A SELF-MOBILE SKELETON IN THE PRESENCE OF EXTERNAL LOADS

by

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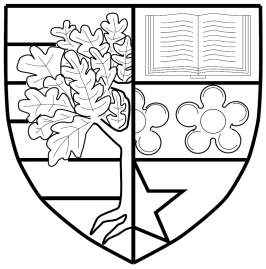

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Abstract

Multicore clusters provide cost-effective platforms for running CPU-intensive and data-intensive parallel applications. To effectively utilise these platforms, sharing their resources is needed amongst the applications rather than dedicated environments. When such computational platforms are shared, user applications must compete at runtime for the same resource so the demand is irregular and hence the load is changeable and unpredictable.

This thesis explores a mechanism to exploit shared multicore clusters taking into account the external load. This mechanism seeks to reduce runtime by finding the best computing locations to serve the running computations. We propose a generic algorithmic data-parallel skeleton which is aware of its computations and the load state of the computing environment. This skeleton is structured using the Master/Worker pattern where the master and workers are distributed on the nodes of the cluster. This skeleton divides the problem into computations where all these computations are initiated by the master and coordinated by the distributed workers. Moreover, the skeleton has built-in mobility to implicitly move the parallel computations between two workers. This mobility is data mobility controlled by the application, the skeleton. This skeleton is not problem-specific and therefore it is able to execute different kinds of problems. Our experiments suggest that this skeleton is able to efficiently compensate for unpredictable load variations.

We also propose a performance cost model that estimates the continuation time of the running computations locally and remotely. This model also takes the network delay, data size and the load state as inputs to estimate the transfer time of the potential movement. Our experiments demonstrate that this model takes accurate decisions based on estimates in different load patterns to reduce the total execution time. This model is problem-independent because it considers the progress of all current computations. Moreover, this model is based on measurements so it is not dependent on the programming language. Furthermore, this model takes into account the load state of the nodes on which the computation run. This state includes the characteristics of the nodes and hence this model is architecture-independent.

Because the scheduling has direct impact on system performance, we support the skeleton with a cost-informed scheduler that uses a hybrid scheduling policy to improve the dynamicity and adaptivity of the skeleton. This scheduler has agents distributed over the participating workers to keep the load information up to date, trigger the estimations, and facilitate the mobility operations. On runtime, the skeleton co-schedules its computations over computational resources without interfering with the native operating system scheduler. We demonstrate that using a hybrid approach the system makes mobility decisions which lead to improved performance and scalability over large number of computational resources. Our experiments suggest that the adaptivity of our skeleton in shared environment improves the performance and reduces resource contention on nodes that are heavily loaded. Therefore, this adaptivity allows other applications to acquire more resources. Finally, our experiments show that the load scheduler has a low incurred overhead, not exceeding 0.6%, compared to the total execution time.

In the name of Allah, Most Gracious, Most Merciful,
<< Taught man what he did not know >> (Qur'an, 95:5)

<< My Lord, enable me to be grateful for Your favour which You have bestowed upon me and upon my parents and to do righteousness of which You approve. And admit me by Your Mercy into [the ranks of] Your righteous servants. >> (Qur'an, 27:19)

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To my country Syria and people who suffered from long years of displacement and suffering. To the martyrs, detainees and all innocent people who are suffering throughout these years.

This thesis is therefore dedicated to them.

Contents

List of Tables

List of Figures

Chapter 1

Introduction

1.1 Context

In recent years, there has been a dramatic increase in the amount of available compute and storage resources. Emerging multicore clusters offer popular high performance computing platforms for commercial and scientific applications. These clusters are either dedicated or non-dedicated. Dedicated clusters are expensive and rare resources while non-dedicated clusters provide sharing resources amongst multiple applications.

The increasing availability of shared resources on parallel platforms associated with the growing demand for parallel applications leads to load variations and resource contention. Resource contention occurs when multiple processes or threads are sharing and competing to acquire processing units. Such contention has a major impact on the performance of the running applications. Hence, resource contention implicitly leads to poor performance, high energy consumption, and application slow down and high latency.

In this thesis, we address the problem of exploiting non-dedicated multicore clusters taking into consideration resource contention under unpredictable workloads. To achieve a desired performance, a framework has been proposed to solve problems and run algorithms in the shortest time in the presence of external load. This framework is designed using skeletal programming approach. This approach is able to manage the complexity of developing parallel computational applications and ex-

ploit easily a parallel computing platform. In this context, our skeleton/framework works as a user-space parallel application that maintains to divide the problem into sub-problems, computations, and run them on the nodes of the cluster concurrently where the skeleton has distributed components hosted on these nodes to harness the computing power of the multicore cluster.

To be adaptive to the variations of the competitive workload, a *scheduling policy* has been provided. As a result, this scheduler is *load-aware*, *performance-oriented* where it takes into consideration the external load and performs pre-emptive scheduling of the parallel computations to meet the performance goal, reducing the total execution time.

Because the variations of workload are changeable and unpredictable, gathering system information to perform better rescheduling decisions is needed along with a dynamic mechanism that takes appropriate decisions. Accordingly, the scheduler uses a measurement-based performance cost model to predict the behaviour of the parallel computations on a running architecture by deriving a mathematical formula that expresses the completion time of the given computations. In this model, we address architecture specific metrics such as resource usage and availability. Furthermore, the behaviour of the parallel computations and network status are also considered.

The rescheduling behaviour of our skeleton is implemented using a pre-emptive approach. This approach requires moving the live computations amongst the nodes of the clusters looking for better computational power to serve these computations faster. The skeleton is enhanced with a built-in mobility support implemented implicitly in the skeleton. The mobility of the skeleton computations is driven by the CPU load of the nodes where those computations run. So once a node becomes highly loaded, a move will be produced for better utilisation of computational resources of that node and to meet the application performance goal. Mobility is an appropriate solution when resource contention happens.

Thus, our *research question* is how can we enable parallel programs to adapt to a dynamically changing environment, to minimise effects on run-times? To sum-

marise our answer, this thesis proposes a data-parallel generic skeleton that is able to harness the computational power of non-dedicated multicore clusters taking into account resource contention in the presence of external loads. This skeleton seeks to find the best computational power to execute its computations faster. Hence the performance goal of the skeleton is application-specific. This makes our skeleton selfish in meeting its performance metric which is sometimes bad in terms of shared computing platforms. But, our experiments show that the skeleton somehow improves the global load balancing and application throughput of the whole system. Moreover, the experiments suggest that the skeleton is scalable and produces speed-up when running different problems. Also, the experiments show significant improvement of the performance and how the skeletons compensate for the load variations. Our skeleton can be used by programmers to solve problems in parallel.

1.2 Contribution

The contributions of this research are as follow:

- We present a data-parallel skeleton called HWFarm for multicore clusters. Multicore clusters provide standard general purpose platforms in terms of computing. This skeleton is designed using Master/Worker pattern and implemented using the C programming language and MPI as a communication library for distributed memory architectures. Therefore, this skeleton works best in parallel platforms compatible with MPI. For local collaboration on the nodes, the PThreads library has been used. This skeleton reallocates its computations/tasks amongst the involved nodes using a built-in mobility approach. This approach uses strong mobility with data mobility where the skeleton saves the execution state of its computations, transfers them, and resumes their execution. Experiments showing the mobility behaviour of the skeleton tasks suggest that the skeleton is able to improve the performance when running problems over shared parallel environments under high loaded conditions. Our experiments show that the HWFarm skeleton is able to mitigate the resource contention by dynamically moving its tasks across the nodes

of the cluster.

- To manage the mobility behaviour of the skeleton, we provide the HWFarm skeleton with a load scheduler which is autonomously responsible for taking mobility decisions and managing load information. The mobility decision is taken using a performance cost model that uses dynamic measures obtained from the environment, the running program, and the load state of the system. The cost model is dynamic where the external load changeable and unpredictable at run-time. The environment measures are the characteristics of the nodes where the skeleton runs. Moreover, the information of the running program includes the progress of the program. Finally, the load state reflects the current internal and external load. The load state is crucial in taking movement decisions. Consequently, this model is dynamic, problem-independent, language-independent, and architecture-independent. This enhances the adaptivity of the HWFarm skeleton.

- We explore a mechanism to generate artificial CPU loads to degrade system performance on multicore architectures and control the resource usage. This leads to a novel load function which may be instantiated to generate predictable patterns of load in a dedicated system to simulate different controllable load scenarios that may occur in a shared distributed non-dedicated system. The generated load is dynamic, precise and adaptive. We present a new tool which helps in evaluating experiments that depend on changes in the load in multi-processor and multi-core environments. Examples of experiments that can be evaluated using the load function are the static/dynamic load balancing, work stealing and mobility experiments. This tool might be used in a homogeneous setting to simulate a heterogeneous environment by giving differential constant loads to the processing elements with the same characteristics. It might also be used to simulate different patterns of system component failure by giving processing elements infeasibly large loads.

1.3 Thesis Structure

The structure of this thesis is as follow:

Chapter 2 introduces concepts of parallel computing, skeletal programming, mobility, scheduling, and cost modelling. Furthermore, this chapter provides a survey of skeletons and parallel programming languages that support the skeletal-based approach.

Chapter 3 gives an overview about designing skeletal-based systems. Then we propose the design of the HWFarm skeleton and the implementation of our skeleton. Furthermore, we explore how we support our skeleton with a mobility mechanism that enables it to move its live computations amongst nodes. Moreover, we discuss the usability of this skeleton and provide guides about how to run different types of problems with some assumptions/restrictions.

Chapter 4 introduces the performance cost model used in the HWFarm skeleton. This chapter describes how the cost model is aware to the environment load state and the computation behaviour. Furthermore, experiments are performed to evaluate the decisions taken by this cost model. These experiments show the accuracy of these decisions in terms of completion times, mobility decisions and mobility costs. Furthermore, this chapter shows that these decisions lead to improve of the performance of the skeleton and meet the performance goal.

Chapter 5 proposes the load scheduler used in the HWFarm skeleton. This scheduler uses a circulating approach to diffuse the load information in order to provide the most recent load information to all participated nodes. Moreover, this chapter discusses in depth how this scheduler uses a measurement-based cost model to take movement decisions that can be used to produce a new schedule. Evaluation experiments have been carried out to demonstrate the improvement of the performance and the mobility behaviour. This chapter also demonstrates that the scheduling and cost operations incur low overhead compared to the total execution time.

Chapter 6 presents a tool implemented as a load function that generates dynamic, adaptive load patterns across multiple processors. This load function is

highly effective in a shared dedicated system for simulating patterns of load changes. Moreover, this chapter shows that this function has minimal impact in an experimental setting.

Chapter 7 explores the evaluation of HWFarm on a range of applications with different characteristics. It also demonstrates the usability of the skeleton over large scale applications. Furthermore, this chapter evaluates the adaptivity feature of the HWFarm skeleton that has a large positive impact on all applications running on shared nodes.

Chapter 8 gives a summary of the thesis, outlines the research direction for future work, and discusses the limitations of this work.

1.4 Publications

This work has led to three publications. The first paper explains the HWFarm skeleton design and implementation with its mobility behaviour. The second paper presents the load function structure and its usability. The third paper propose the dynamic cost model and the load scheduler to improve the performance eof the HWFarm skeleton. These published papers are:

- Alsalkini T. and Michaelson G., 2012. Dynamic Farm Skeleton Task Allocation through Task Mobility. In: 18th International Conference on Parallel and Distributed Processing Techniques and Applications. Las Vegas, USA, pp. 232-238.

- Alsalkini T. and Michaelson G., 2014. Generating Artificial Load Patterns on Multi-Processor Platforms. In: 11th International Conference on Applied Computing. Porto, Portugal, pp. 77-84.

- Alsalkini T. and Michaelson G., 2015. Optimising Data-Parallel Performance with a Cost Model in The Presence of External Load. In: 12th International Conference on Applied Computing. Greater Dublin, Ireland, pp. 89-96.

Chapter 2

Literature Review

Hardware development has been progressing in the recent years. However, the rise of multi-core processors has affected the ability of the software developers to harness the resources of these architectures to match their requirements. Designing parallel and distributed software models to manage the scientific problems is needed to fully exploit such platforms. These models should offer abstractions of low-level details to free the developers from this burden. In this thesis, we propose a parallel framework that aims to harness the compute power of multi-core clusters. In Sec 2.1 we review the development of the architectures and parallel computing as well as computing platforms used to run parallel applications. Furthermore, the parallel programming models needed to fully exploit such platforms are discussed. This framework is proposed as a skeleton that encapsulates all coordination and low level issues. This helps the programmers to focus on their problem rather than spending too much time dealing with parallel programming details. Algorithmic skeletons are high-level parallel programming constructs that embed parallel coordination over sets of locations. A background of algorithmic skeletons and a survey of skeletal-based libraries/languages have been shown in Sec 2.2. Our skeleton addresses the resource contention issue in shared platforms. This requires a scheduling policy that deals with the changeable load conditions in the system and takes appropriate decisions. Dynamic cost modelling and performance models used in the skeletal based frameworks and structured parallel models are introduced in Sec 2.3. The notions of scheduling and their techniques are discussed in Sec 2.4. Finally, the skeleton

performs rescheduling activities by moving some parallel computations amongst the nodes of the clusters. This movement happens autonomously and controlled by the scheduler. Sec 2.5 reviews the concepts of mobility and autonomous systems.

2.1 Parallel Computing

Parallel computing solves big computational problems by concurrently using multiple processing elements. Parallelism aims to reduce the total execution time by decomposing the problem into independent sub-problems and executing them simultaneously on a parallel computing platform. Thus, parallelism seeks to achieve better computational performance.

2.1.1 Parallel Architectures

Parallel computing architectures are the platforms where the computations are concurrently executed. These architectures are composed of multiple processing elements, which are connected via some interconnection networks, and software that manages those elements to work together [93]. The processing units communicate with each other using either distributed or shared memory approach. See Figure 2.2 and 2.1 that show the components of distributed and shared memory architectures, respectively.

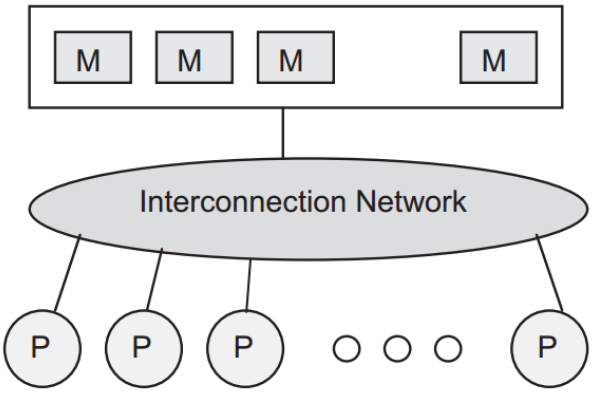


Figure 2.1: Shared Memory Architectures.

The most popular classification of computer architectures was defined by Flynn [100]. In this taxonomy, there are two types of streams: the data stream and

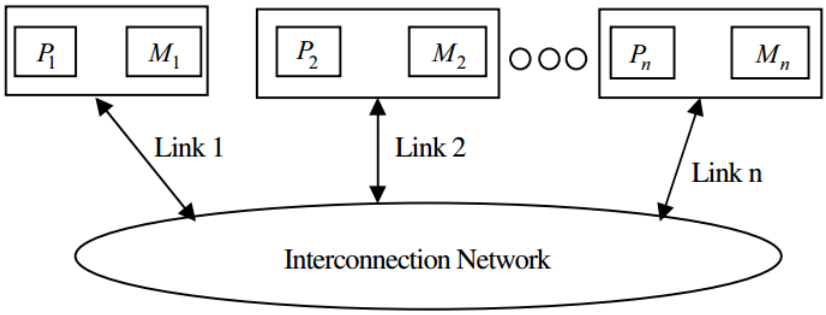


Figure 2.2: Distributed Memory Architectures.

the instruction stream. These streams can be single or multiple. As a result, the computer architecture categories are: Single-Instruction Single-Data (SISD), Single-Instruction Multiple-Data (SIMD), Multiple-Instruction Single-Data (MISD), and Multiple-Instruction Multiple-Data (MIMD). The single-processor computers are classified as SISD systems while the parallel systems are either SIMD or MIMD.

However, we here introduce a survey of parallel architecture and their parallel programming models according to memory access. Recent surveys can be found in [21, 138, 82].

2.1.1.1 Distributed Memory Architectures

Distributed memory systems are parallel architectures in which each processor unit has only access to its own local memory. The processing units of distributed memory architectures are connected in several ways ranging from architectural-specific structure to geographical spread networks. Examples of these systems are:

- *Distributed Memory Multiprocessor*:

  Distributed memory multiprocessor systems consist of multiple processing elements that connect to each other via interconnection networks. In these systems, there is no global memory, so that the processor needs message passing approach to access remote data [181].

- *Multicomputer*:

  A multicomputer is a distributed memory multiprocessor where the processors are physically close to each other and connected through high-speed intercon-

nection network [19].

- *Clusters*:

  A cluster is a parallel computing system that consists of a set of computers interconnected with each other by a network to comprise a computing system [49]. Each computer in a cluster may have a single processor or multiple processors and connects to other computers via a LAN (Local Area Network). The nodes, the computers in the cluster, can work together as an integrated computing resource or they can operate individually. Hence, clusters provide cost-effective environments that offer computing services for solving high performance problems. An example of a cluster is a Beowulf system which is a scalable cluster hosted by open source software [209]. A Beowulf system is composed of group of nodes incorporated in personal computers and based on a private system network. In this thesis, we are studying this architecture as one of parallel computing platforms.

- *Grid*:

  A Grid is a system for sharing the computational resources, such as data storage, I/O capacity, or computing power, over the Internet [102, 103]. A computational Grid is a mechanism to access shared computational resources in a scalable, secure, high-performance manner. Those who use a Grid are able to share and use computational resources in geographically distributed locations.

2.1.1.2 Shared Memory Architecture

A shared memory system is a category of parallel architectures where each processing unit has access to a global memory. Through this memory, the processes communicate, coordinate, and synchronise with other processes in the system [93]. In such systems, there are independent processors connected with memory modules via an interconnection network. In terms of memory access, shared memory systems can be categorised in three categories:

- *Uniform Memory Access (UMA)*: In UMA, the shared memory locations are

accessible by all processors with the same access time. These systems are also known as Symmetric Multiprocessor (SMP). An Example of this architecture is PMC-Sierra RM9000x2 [192].

- *Non-uniform Memory Access (NUMA)*: NUMA is a memory organisation where each processor has part of the shared memory. In these systems, the access times are not equal due to the distance between the processor and the memory module. For an example, see the Intel Single-chip Cloud Computer (SCC) [164].

- *Cache-Only Memory Access (COMA)*: In COMA, the shared memory comprises cache memory and the address space is made of all the caches. In this case, part of the shared memory and a cache directory are attached to each processor. The Swedish Institute of Computer Sciences Data Diffusion Machine (DDM) [113] is an example of this architecture. Another example is KiloCore [39] which is a chip that has 1000 cores and 12 memory modules. This chip is developed by the VLSI Computation Laboratory (VCL) at UC Davis.

2.1.1.3 Multi/Many-core Architectures

Computer manufacturers initially made chips with one processor. Producing faster processors requires increasing the number of transistors and raising the clock speed. Due to the limit on the scaling of clock speeds, which is known as the power wall, manufacturers turned to multicore architectures to overcome the space and overheating issues. In this architecture, the chips have two or more processors (cores) and share hardware caches [120]. Multicore architecture is an effective example of a shared memory architecture where the communication amongst cores is fast and the bandwidth is high.

Another core-based approach has been introduced in parallel programming. This approach, which is known as many-core, uses a large number of small cores. An example of a many-core architecture is the Graphical Processing Unit (GPUs) [125] where a GPU is a special-purpose SIMD processor initially designed for a particular

class of applications [178]. Recently, GPUs have been employed to perform general purpose applications GPGPU [232].

2.1.2 Parallel Programming Patterns

Effective use of parallel architectures involves dividing a problem into computations that can be of executed on available processing units. Parallelising a problem can be several kinds: data, task, or pipeline parallelism [163, 119].

In terms of parallel programming design, Mattson el al [163] introduced a pattern language that provides patterns to help users in developing parallel programs. This language has 19 patterns organised into four design phases: Finding Concurrency, Algorithm Structure, Supporting Structures, and Implementation Mechanisms. However, the patterns that support structure design and correspond to the parallel programming models are: SPMD (Single Program Multiple Data), Master/-Worker (task pool), Loop Parallelism (independent iterations), and the Fork/Join pattern.

- *SPMD*: In this pattern, each process or thread, performs the same operations but with different set of data. SPMD can be used either in distributed or shared memory systems. This pattern provides processes that are easy to manage, achieves high scalability, and shows close to parallel environment.

- *Master/Worker*: This pattern involves two kinds of processes: Master processes and worker processes. A master process initiates a bag of tasks and sets a pool of workers. Whilst, a worker process obtains a task from the master and executes it. All workers run concurrently until the bag becomes empty. This pattern is typically used in problems that require the workload to be balanced amongst the workers. The Master/Worker pattern has good scalability and fault tolerance support. A disadvantage of this pattern is the bottleneck between master and workers but this problem can be avoided if the algorithm is well implemented.

- *Loop Parallelism*: In this pattern, the runtime will split up the intensive iterations amongst the processes or threads if they are nearly independent. Loop parallelism is mainly suitable for shared memory systems. But it also can be used in a distributed fashion if each loop iteration is really big.

- *Fork/Join*: This pattern has a main process that creates new processes to execute some concrete operations. The main process will wait for all forked processes to join. The Fork/Join pattern is suitable for problems that create tasks dynamically and good for shared systems. The overhead in this pattern is related to the cost of creating and destroying the processes.

2.1.3 Parallel Programming Models

Developing parallel applications in a wide range of parallel systems is a complicated task [49]. Developers are challenged by a variety of issues related to the system and the programming style. To solve these issues, there are two main approaches: automatic parallelization and parallel programming [138].

The first approach relies on parallelizing compilers that are used for parallelizing a sequential program into a version able to execute on a parallel system. Such compilers are limited to problems that have regular computations and commonly do not provide useful speedup on distributed memory machines [49]. An alternative to parallelizing compilers is parallel programming languages which are used to relieve programmers from the complexity of parallelism. However, these languages are designed from principles that help to produce a parallel programming language to deal with the difficulties of parallelism.

The second approach is parallel programming which is based on developer efforts to exploit parallel architectures. In this approach, developers use a traditional high-level programing language, like C or Fortran, augmented with a library, such as PThreads [48], or extended with parallelism support, like CILK [37].

Other ways of parallel programming are providing programming skeletons that support some parallelization. Skeletal programming will be explained in further details later.

As mention above, parallel architectures are categorised into shared memory and distributed memory [207]. Here, we discuss the parallel programming models used to develop across parallel systems.

2.1.3.1 Distributed Memory Systems

The message passing model is commonly used in distributed memory systems to move data between processing elements without the need for a global memory. Programming using the message passing model has the advantages [85]: portability of parallel programs as they do not require any hardware support, and the ability to explicitly control the placement of data on the memory by the programmer. This model also has disadvantages [49, 85]. The first one is that the programmers have to manage the tasks of parallelisation, such as: communication, synchronisation, data distribution, and load balancing. The second disadvantage is that these models may incur communication overhead due to the time needed for processes to communicate. Message passing model suits the SPMD parallel programming pattern in addition to the Master/Worker pattern [163].

Examples of message-passing models:

- *MPI*: Message Passing Interface is a library of routines to connect processes that are located across the distributed memory system [112]. This library can be bound to C, C++, Fortran, Java, etc. MPI operations are classified as point-to-point and collective routines. Point-to-point routines, such as send/receive, provide communication between two processes. Collective routines ease communication amongst groups of two or more processes.

- *PVM*: Parallel Virtual Machine is a software environment that uses the message passing model to exploit heterogeneous distributed processing elements. PVM makes a set of computing units appear as a virtual computing system [27].

2.1.3.2 Shared Memory Systems

In shared memory systems, processes or threads, which execute tasks concurrently, have access to a global shared memory [93, 19]. The communication amongst processes can be accomplished through shared variables or shared communication channels. Shared memory architectures have low latency and high bandwidth. However, this raises two issues: consistency and coherency [85]. The consistency issue is raised when multiple processors try to access or update shared memory locations. Therefore, a proper memory coherence model should be chosen in designing distributed memory systems.

Examples include:

- *POSIX Threads (Portable Operating System Interface Threads)*: In this model, there are several threads, running simultaneously on a shared memory platform [19]. PThreads [48] is introduced as a low level, flexible library of routines to manage the threads explicitly. This library is used with the C programming language. Using PThreads, programmers have full control to create, manage, and destroy threads. Parallelism using this model needs much effort from developers to avoid race conditions and deadlock. The most appropriate parallel programming pattern when using this library is the Fork/Join model [163].

- *Intel TBB (Intel Threading Building Blocks)*: Intel TBB is a multithreaded model in shared memory systems [191]. It is presented as a C++ template library that manages and schedules threads to run concurrently in order to execute tasks in parallel. This library also contains various generic algorithms and supports dependency and data flow graphs as well as offering synchronisation and collective primitives.

- *OpenMP (Open Multi Processing)*: OpenMP is a shared memory based parallel programming model; it is also known as a multithreaded model [57]. OpenMP is implemented as an API to provide a set of compiler primitives and runtime library routines. This API can be used with Fortran, C, and C++. The parallel program patterns that are suited to OpenMP are loop parallelization,

SPMD, and join/fork pattern.

To combine the ease of writing parallel programs in shared memory systems with the scalability of the distributed memory environments, the DSM (Distributed Shared Memory) model has been proposed [185]. In this model, the system is implemented as shared memory in a distributed memory environment. An example of a model that uses the DSM approach is PGAS (Partitioned Global Address Space) [63]. An example of a PGAS language is Chapel [56]. Moreover, UPC (Unified Parallel C) is a parallel programming language that supports the PGAS model. UPC is an extension of the programing language C and can be used in shared or distributed memory environments [220].

For GPU architectures, the SPMD programming model is used as each element is independent from other elements [178]. To develop applications over GPUs, NVIDIA proposed CUDA (Compute Unified Device Architecture) as a parallel programming model [176]. Moreover, OpenCL (Open Computing Language) provides a standard interface to implement data and task parallelism over heterogeneous platforms [212].

2.2 Skeletons for Parallel Computing

The algorithmic skeleton, according to Cole [65], is an approach in parallel programming to abstract the complexities that exist in the parallel implementations. The skeleton concept is closely related to functional languages, so higher order functional structures can be produced by using skeletons [187].

A parallel program can be composed of simple skeletons. These skeletons are referred to as elementary skeletons. These skeletons abstract the basic operations of the data parallel model [159]. Furthermore, elementary skeletons may use performance cost measures to achieve effective implementations. Using elementary skeletons, it is difficult to adapt the architectural characteristics of the wide range of parallel computing systems. Moreover, acquiring the best performance when composing several elementary skeletons is a very tough job. To solve these issues, exact skeletons can be used to define complex patterns.

Each skeleton has an implicit parallel implementation hidden from the user; thus, the main advantage is that the communication and parallelism details are embedded in the skeleton. The skeletons are equivalent to polymorphic higher order functions so that there are various kinds of skeletons covering different programs over different data types [99]. In contrast, skeletons that support particular data structures are known as homomorphic skeletons. Homomorphic skeletons may deal with lists, arrays, trees or graphs. Thus, some authors may name skeletons depending on the data structure that the skeletons support, for example list skeletons, matrix skeletons, or tree skeletons.

2.2.1 Skeleton Types

In terms of functionality, parallel skeletons can be classified into three types: task-parallel, data-parallel and resolution skeletons [187, 111]:

- *Task-parallel skeletons*: In this kind of skeleton, the parallelism will be based on the task, so there are many function calls in parallel. Examples of task-parallel skeleton are: the pipe skeleton where computations that are relevant to different stages can run simultaneously, and the farm skeleton which can schedule independent tasks across several processing units. This is also known as Master/Slave. The pipe skeleton can be found in different frameworks such as SKELib [74] and Muskel [9] while examples of libraries that support the farm skeleton are JaSkel [98] and Eden [152].

- *Data-parallel skeletons*: These skeletons apply parallelism by partitioning the data amongst processors and performing the computation on different parts concurrently. For examples: the map skeleton applies a function or operation concurrently over items in a list. The map skeleton is an example of SIMD parallel programming pattern. The reduce skeleton executes a function or operation on each pair of elements to form the final result. It is also referred as scan. The fork skeleton applies different operations on various data elements. The fork skeleton is an example of a MIMD parallel programming pattern. Most of the libraries support data-parallel skeletons. For examples P3L [73]

offers the map, reduce and scan skeletons while Calcium [51] library support the fork skeleton.

- *Resolution skeletons*: these skeletons are designed as the solution of a family of problems. An example of a resolution-parallel skeleton is Divide and Conquer (D&C) which divides the list of elements recursively into two lists until a condition is met. Then, the D&C skeleton applies a function to the list and afterwards merges the results back to produce the final result. The D&C skeleton is provided in many libraries such as Skandium [149] and Calcium [51]. Another example of resolution-parallel skeletons is Branch and Bound (B&B) which also branches recursively across the search space. Then, it uses an objective function to bound the resulting data. An example of libraries that supports the B&B skeleton is Muesli [62].

2.2.2 Advantage of Using Skeletons

The main target of skeletons in parallel programming is to separate the application from the implementation [99]. By using skeletons, users can specify the parallel parts and leave the parallelism complexities to the skeletons.

Skeletons are modelled as higher-order functions able to be customised to specific applications. However, optimised skeleton implementations, which fit specific languages and parallel architectures, should be generated to achieve high performance and portability over various machines.

The main advantages of using algorithmic skeletons in parallel programming are [49]:

- *Programmability*: Skeletons hide the low-level details, such as communications and coordination, from the programmers. Therefore, such solutions help the programmers to spend more time in optimising the problem. Hence, using skeletons improves the programmability of the parallel programming systems and increases the productivity of users.

- *Reusability*: Skeletons have been built to form generic patterns for developing

the problems that have the same parallel structure. This will increase the reusability and avoid the repetition of efforts in programming and optimising the programs that belong to particular parallel template.

- *Portability*: Portability has considerable importance in parallel applications. So, skeletons should adapt to the parallel systems and the hardware architecture. Thus, parallel applications that are developed using skeletons have ability to run on various platforms.

- *Efficiency*: Developing parallel applications requires a balance between efficiency and portability. Skeletal-based parallel programming using cost models can achieve improvement in the performance.

2.2.3 Skeletons in Parallel Environments

Skeletal programming is used to overcome the problems of coordination in parallel programming by exploiting generic program structures. Much work has been carried out on skeletal programming for different data types for various parallel architectures. Skeleton implementations may support either a specific parallel architecture or heterogeneous architectures, including shared memory, distributed memory, multi-core, or many-core architectures. Such skeletons are provided as libraries on top of a parallelisation mechanism, such as MPI, or a high level parallel language that supports skeletal constructs. Each skeleton may be associated with a compiler that translates the high-level functions into source code able to run over the target hardware. Some implementations may support a list of skeleton patterns: map, reduce, farm, etc. Others may support one or more types of skeletal programming.

In this section, we are going to review some examples of available skeletons and parallel programming languages that support the skeletal approach. Other surveys can be found in [21, 111].

- *P3L, SkIE & SkELib*

  P3L (Pisa Parallel Programming Language), 1992, [73] is a skeleton-based parallel programming language that provides skeleton constructs. These con-

structs abstract the common patterns of task and data parallelism. P3L is associated to a template-based compiler that is used to optimise the implementation of templates to a specific architecture. Moreover, the P3L compiler can use a performance cost model to help in allocating resources corresponding to parallel systems.

SkIE (Skeleton-based Integrated Environment), 1999, [24] is a coordination language similar to P3L. This language enables the user to interact with graphical tools to compose skeletal parallel modules. Furthermore, this language provides advanced tools such as visualisation, performance analysis and debugging tools.

SkELib, 2000, [74], which is a C library, inherits from P3L and SkIE and uses a template-based system.

- *SCL*

  SCL (Structured Coordination Language), 1995, [77] is a skeletal programming language that supports various commonly used data structures through configuration skeletons. Furthermore, SCL offers data-parallel skeletons, like map, and task-parallel skeletons, like farm, using elementary skeletons and computation skeletons, respectively.

- *Skil*

  Skil, 1996, [43] is an imperative language supported with higher-order functions and a polymorphic type system. Skil offers data and task parallelism over parallel distributed architectures. Skeletons in Skil language are not nestable.

- *HDC*

  HDC (Higher-order Divide and Conquer), 2000, [121] is a sub set of Haskell that uses a higher-order functional style. It has many implementations of the Divide and Concur paradigm starting from the general model to concrete cases such as multiple block recursion and elementwise operations. Therefore, it supports resolution parallelism over distributed platforms.

- *Muskel & nmc*

Muskel, 2001, [9], provides nestable skeletons for data and task parallelism and exploits a macro data flow model to achieve parallelism. Muskel gives users a skeletal-based parallel programming system by targeting parallel distributed architectures. Furthermore, Muskel has features that optimise the performance such as load balancing and resource usage. Much work has been done on skeletal extensibility [9] and combining structured with unstructured programming [72].

Nmc, 2010, [10] is the multicore version of the Muskel library. This version provides some skeletons to run on multicore clusters.

- *ASSIST*

  ASSIST, 2002, [223] is a structured programming language that uses a module-described graph to express parallel applications. It has performance optimisation through controlling resource usage and supporting load balancing.

- *SkiPPER*

  SkiPPER, 2002, [198] is a library of skeletons for vision applications in Caml with type safety. Skeletons in SkiPPER are either declarative or operational.

- *Mallba*

  Mallba, 2002, [8] is a skeletal-based library for combinational optimisation. Mallba provides three generic resolution methods: exact, heuristic, and hybrid with three different implementations: sequential, parallel in local area, and parallel in wide area.

- *Llc language*

  Llc, 2003, [87] is a high-level parallel programming language that offers support for four skeletons: forall, parallel sections, task farms and pipelines [8]. Skeletons with Llc can be executed on multicore or distributed systems. Llc uses a compiler that generates MPI code based on OpenMP like directives. A new approach to generate a hybrid MPI/OpenMP code has been developed to control the communication on the node itself and amongst the nodes [194].

- *Alt & HOC-SA*

Alt, 2003, [16, 15] a Java-based Grid programming system composed of a set of skeletons. These skeletons are provided as services to the clients on parallel distributed systems. It supports a data-parallelism approach over shared distributed memory architectures.

HOC-SA (Higher-Order Components-Service Architecture), 2004, [91] encapsulates the Alt approach to support parallelism. In HOC-SA, clients send the code and the data to be executed to servers with a skeleton description flow. Once the execution completes, the result is delivered to the users.

- *Lithium*

  Lithium, 2003, [12] is a Java library that provides nestable skeletons to support data and task parallelism. Lithium is implemented with a macro data flow implementation model. In this model, the nodes in the data flow graph host a piece of code to be executed on the computational units. Extensions of Lithium have been proposed for performance optimisation such as load balancing.

- *Eden*

  Eden, 2005, [152] is an extension of Haskel. It supports task and data parallelism over distributed memory environments. It also supports automatic communication between processes. Many extensions have been proposed for Eden such as a flexible distributed work pool skeleton [83] in 2010 and a skeleton iteration framework [84] in 2012.

- *eSkel*

  eSkel (Edinburgh Skeleton Library), 2005, [29] is a C library that offers a set of skeletons over the MPI model. This library supports data and task parallelism on parallel distributed systems. eSkel provides two skeleton modes, nesting and interaction. In terms of performance, eSkel uses empirical methods and the Amoget process algebra for resource allocation and scheduling.

  The Edinburgh group has done much work on the adaptive approach through presenting a parallel pipeline pattern [110].

- *JaSkel*

JaSkel, 2006, [98] is a skeleton based framework in Java. It provides nestable skeletons that can run on different platforms. JaSkel skeletons execute sequentially, concurrently on shared memory systems, or in parallel on clusters.

- *QUAFF*

  QUAFF, 2006, [97] is a C++ and MPI based skeleton library that uses a template-based meta-programming approach to reduce overhead and enable compile time optimisation. QUAFF provides a set of nested skeletons on parallel distributed environments. Moreover, QUAFF uses type checking and C++ templates to generate new C/MPI code at compile time.

- *SkeTo*

  SkeTo, 2006, is a C++ library that provides a set of operations on parallel data structures, such as list, on distributed memory systems [162]. This library provides parallel skeletons based on the BMF programming model [32]. SkeTo supports nestable skeletons for data and resolution parallelism. To optimise SkeTo, a fusion transformation approach has been provided in order to reduce the overhead. A new version of SkeTo has been proposed in 2009 to work on multicore architectures [136]. In the multicore version, SkeTo offers a number of skeletons that manage the dynamic scheduling using the size of cache. Recently, a new version with list support has been released [160] in 2010. In this version, the skeletons are equipped with fusion optimisation that is implemented based on an expression templates programming technique.

- *AMSs*

  AMSs (Autonomous Mobility Skeletons), 2007, [80] are higher order functions that support autonomous mobility. These skeletons are guided by a cost model which makes them aware of the load changes on the network.

- *Calcium*

  Calcium, 2007, [51] is a library of skeletons in Java. This library supports nestable data and task parallel skeletons on parallel distributed architectures. Moreover, Calcium provides additional features that help in improving the

performance such as a performance tuning model.

- *TBB*

  TBB (Threading Block Building), 2007, [191] is a pattern-based library, developed by Intel, for parallel applications on multicore architectures. TBB provides a wide range of parallel patterns such as, for, reduce, sort, in addition to some patterns. TBB offers concurrent data structures and gives the programmer ability to control other threads, task scheduling, and granularity. Major industry powerhouses have developed similar frameworks, TPL, 2009, [147] from Microsoft, MapReduce, 2008, [79] from Google, Hadoop, 2012, [228] and Phoenix, 2007, [189] from Apache, and BlockLib, 2008 [14] from IBM.

- *Muesli*

  Muesli, 2009, [62] is a skeleton library that offers skeletons through C++ methods. This library provides nestable skeletons for data and task parallelism and supports parallel distributed architectures. Muesli was extended in 2010 to support multicore parallel programming [61].

- *Skandium*

  Skandium, 2010, [149], like Calcium, is also a Java library that supports skeletal programming on shared memory systems. This library is a reimplementation of the Calcium library on multicore architectures. Skandium offers nestable skeletons for both data and task parallelism.

- *STAPL*

  STAPL (Standard Template Adaptive Parallel Library), 2010, [47] is a skeleton framework that gives the user the ability to compose a parallel program from a set of elementary skeletons. Using a parametric data flow graph, this framework is a representation of a parallel implementation of STL (Standard Template Library). STAPL can work in both shared and distributed memory platforms. Furthermore, this framework supports nested composition for multi-level parallelism.

- *FastFlow*

FastFlow, 2011, [11] is a parallel programming framework written in C++. This framework supports pattern-based programming on parallel shared/distributed memory systems in addition to GPU architectures. FastFlow is structured into three layers to provide different levels of abstractions to the application developer. These layers give the programmer a high level parallel programming, flexibility, and portability to different platforms. In 2014, a ParallelFor skeleton [75] was added to the framework that supports many-core architecture. This skeleton filled the gap between the conventional data structures and loop parallelisation facilities provided by low-level frameworks, such as OpenMP.

- *OSL*

  OSL (Orlans Skeleton Librray), 2011, [128] is a C++ library of data-parallel skeletons that follow the BSP parallel model [36] of parallel computations. It is built over MPI and uses expression templates to optimise the efficiency in a functional programming style. Skeletons in the OSL library perform operations on distributed arrays where the data is distributed amongst the processors. In an update of this library, in 2013, a skeleton has been implemented to support list homomorphism. This skeleton is called BH [146] (BSP homomorphism). Like SkeTo, OSL also uses expression templates for fusion optimisation.

- *HWSkel*

  HWSkel, 2013, [21] is a skeletal based parallel programming library for heterogeneous multicore cluster and GPUs. HWSkel provides a number of skeletons optimised through a static performance model.

- *Skel*

  Skel, 2014, [46] is a domain specific language implemented in Erlang. This library supports map, farm, pipe and seq skeletons as well as providing a high-level cost model related to each skeleton. This cost model predicts the performance of the parallel program. Skeletons of Skel can be nestable where they run over shared memory platforms.

- *SkelCL*

  SkelCL, 2015, [210] is skeleton library for GPUs to ease GPU programming. Other examples of skeleton-based GPU programming frameworks are PSkel, 2015, [183], SkePU, 2010, [94], Marrow, 2013, [158], and Lapedo, 2016, [127].

Much work has been done to compose the memory affinity approach with skeletal programming. Such skeletons seek to enhance the memory affinity by locating the threads and the data for increasing the performance. Recent work can be found in [109].

Some skeletons libraries have been developed for embedded real-time systems [208].

Another approach to skeletal programming is developing an implementation of an existing library. Example of these approach are DatTel [35] and MCSTL [203], which are parallel implementation of the standard library STL in C++.

Several researchers developed skeletons with various programming languages. Surveys of work on skeletal programming can be found in [111, 21, 197, 190, 35, 161, 170, 68].

See Table 2.1 that summarises all skeleton mentioned in our survey.

2.3 Parallel Cost models

A cost model is a performance model [166] used to estimate the costs of program performance metrics, such as time [193]. Cost models have two levels [80]:

- Computation Cost Model: to estimate the cost of a sequential computation.
- Coordination Cost Model: to estimate the cost of coordinating of parallel, distributed and mobile programs.

Computation Cost Model

The estimation of execution time for a program running on a specific computer and manipulating some data can be done in two ways [64]:

	Year	Type of Support	Nesting	Skeleton Set
P3L, SkIE & SkELib	1992-2000	language/ library(SkELib)	limited	map, reduce, scan, comp, pipe, farm, seq & loop
SCL	1995	language	limited	map, scan, fold & farm
Skil	1996	library	no	pardata, map & fold
HDC	2000	Haskell subset	no	map, red, scan, filter & dc
Muskel & nmc	2001	library	yes	farm, pipe & seq
ASSIST	2002	language	no	seq & parmod
SkiPPER	2002	library	limited	scm, df & tf
Mallba	2002	library	no	exact, heuristic & hybrid
Llc language	2003	language	yes	forall, parsection, farm & pipeline
Alt & HOC-SA	2003-2004	library	no	map, reduction, scan, dh, apply & sort
Lithium	2003	library	yes	map, farm, reduce & pipe
Eden	2005	Haskell extension	yes	map, farm, dc, pipe & ring
eSkel	2005	library	yes	pipe, farm, deal, butterfly & hallowSwap
JaSkel	2006	library	yes	farm, pipeline & heartbeat
QUAFF	2006	library	yes	seq, pipe, farm & pardo
SkeTo	2006	library	yes	list, matrix & tree
AMSs	2007	library	no	automap, autofold & autoIterator
Calcium	2007	library	yes	seq, pipe, farm, for, while, map, dc & fork
TBB	2007	library	yes	for, reduce, scan, do, sort & pipeline
Muesli	2009	library	yes	array, matrix, farm, pipe & parallel comp
Skandium	2009	library	yes	seq, pipe, farm, for, while, map, dc & fork
STAPL	2010	library	yes	map, map-reduce, scan, butterfly, allreduce & alltoall
FastFlow	2011	library	yes	pipeline, farm, parallelFor & mapReduce
OSL	2011-2013	library	no	map, zip, reduce, scan, permute, shift, redistribute & flatten
HWSkel	2013	library	no	hMap, hMapAll, hReduce, hMapReduce & hMapReduceAll
Skel	2014	language	yes	map, farm, pipe & seq

Table 2.1: Skeletons summary.

- *Static Analysis*: The measurement is done by using mathematical reasoning on the code of the program and the data to determine the time to execute the program. The performance model of the program may be machine-independent. These models are also called static cost models or analytical formula.

- *Dynamic Analysis*: The execution time of a program is measured on given data and on a particular machine. The measurement is done by using an internal clock and benchmarking the execution of the program where the benchmark is machine-specific. These models are also called dynamic cost models.

Coordination Cost Models

Parallel programming is a complex activity that includes many decisions, such as task allocation, scheduling and communication. The parallel programming model can exploit the coordination cost models for parallel programming. Coordination models may use the computation cost models for enhancing coordination decisions.

To simplify using a cost model with parallel programs, developers use constrained parallel programming paradigms to simplify modelling the coordination in a parallel application.

2.3.1 Constrained Parallel Programming Paradigms

To make a parallel programming solution efficient, the programmer should take care of the coordination amongst the resources. However, programmers may typically use constrained coordination patterns to ease the challenges of developing parallel applications [219]. By using these coordination models, resource analysis will be more flexible.

Bulk Synchronous Parallel

The BSP model uses a coordination pattern where the computations are composed of a series of supersteps [123]. In a BSP computation, each superstep includes three stages: independent computations, communication, and barrier synchronisation. In

the first stage, independent computations run on each processor where each computation concurrently performs some operations on local data. In the communication stage, data from each processor will be exchanged with other processors. The barrier synchronisation stage blocks all processes and waits for other processes until they finish their computations and communication.

The Bird-Meertens Formalism

Programmers in BMF [32] are constrained to use a set of higher-order functions, HOFs. BMF is a calculus that uses bulk operations over data structures, such as lists, to derive a functional program form specification. Rangaswami [188] proposed the HOPP model (Higher-order Parallel Programming) which is a methodology based on BMF.

Workflow Language

Using workflow languages [227], such as Pegasus [145], programmers are able to manage the execution of computations on available resources. Such a language maps an abstract workflow written by the user or constructed using Chimera [104] which is a system that describe the logical input, the transformation, and the output.

Skeletons

As discussed above, common coordination models are encapsulated in constrained patterns with associated cost models to be used by the programmers. These patterns can be proposed as a library or language constructs.

2.3.2 Cost Models

Parallel cost models are used to predict the behaviour of a parallel application on a running architecture by deriving a mathematical formula that depicts the execution time of the given application. This formula is parameterised with a set of parameters that reflect the characteristics that affect the program execution. These metrics can be provided by the programmer or by the environment.

Cost models are usually employed by structured frameworks, such as skeletons, to enhance the performance or by schedulers to increase the accuracy of their decisions.

In the following, we will show some parallel performance models for parallel systems. Other surveys can be found in [219, 21, 155, 115, 133, 179].

2.3.2.1 PRAM Cost Models

The PRAM, Parallel Random Access Machine, model [101] is an abstraction of parallel computation by assuming that PRAM operations run synchronously on a set of processors with global shared memory. The PRAM model is based on a sequential model RAM [70].

Computations in the PRAM model are composed of synchronous steps; each costs a unit of time regardless of the operation and wherever the location of shared memory is. This helps in design-time analysis of the parallel algorithm where the communications and the memory hierarchy are not needed to be addressed at this phase of design to expose application-specific parallelism.

In real machines, the cost of a parallel algorithm may be affected by a number of parallel activities, such as memory access and network latency. Thus, several variants of PRAM model have been proposed. Block PRAM (BPRAM) [5], Local memory PRAM (LPRAM) [6], and Hierarchical PRAM (H-PRAM) [122] are PRAM-based variants for addressing the remote memory and data locality. Asynchronous PRAM (APRAM) [69] is another PRAM variant that introduces the asynchrony concept to the basic PRAM model. Concurrent shared memory access is addressed through the variants [168]: Queue-Read Queue-Write PRAM (QRQW PRAM), Exclusive-Read Exclusive-Write PRAM (EREW PRAM) , and Concurrent-Read Concurrent-Write PRAM (CRCW PRAM).

2.3.2.2 LogP Cost Models

The LogP model [71] is a parallel computation model for distributed memory systems. In this model, a parallel machine is composed of a number of processors that have access to local memory and communicate with other processors via message passing. The communication costs are described in the LogP model using four

parameters: L(latency), o(overhead), g(gap), and P(processors).

- Latency, L, is the maximum communication time needed to send a message between two processors. It may depend on the hierarchy of the architecture.
- Overhead, o, is the amount of time required by a processor to receive and send a message. Within this period, the processor cannot perform other activities.
- Gap, g, describes the minimal amount of time between receiving or sending two messages. The inverse of gap is the communication bandwidth which is the amount of data that can be exchanged within a period of time.
- Processors, P, is the number of processors in the system. Furthermore, P indicates the degree of parallelism.

The LogP model supports only short messages and ignores long messages. To overcome this shortcoming, an extension of the basic LogP model, LogGP model, has been proposed by Alexandrov [13]. In this model, a new parameter G reflects the bandwidth with regard to long messages.

Supporting long messages in LogGP raised an issue related to the increased overhead incurred by the synchronisation cost between the sender and the receiver. These costs have been described by the LogGP extension, LogGPS [126].

Memory access in the LogP model is also characterised where the costs of access are the same for all memory locations. That may be true in homogeneous architectures, such as clusters. But the costs may be different for heterogeneous systems. To model these costs, HLogGP [42], an extension of LogGP, has been developed.

The LogP model offers a compromise between abstraction and simple models, such as PRAM. However, LogP characterises the communication and coordination costs to give a more realistic view of the performance implementation for algorithms that need likely communications.

2.3.2.3 BSP Cost Models

The BSP cost model [205, 221] uses restricted BSP programming to fairly predict the performance of computations. The BSP model provides a bridge that links the

software and hardware. Moreover, this model offers a simple way to derive the values of model parameters for a specific machine for realistic prediction on several parallel architectures.

Due to the simplicity of the BSP programming model which consists of a sequence of supersteps, the cost of a BSP program equals the sum of the costs of each superstep.

The BSP cost model estimates the cost of each superstep using this formula:

$$T_{superstep} = w + h.g + l$$

Where:

w: the cost of the longest superstep (running local computation).

h: number of messages between two processors.

g: an estimated value that depends on the communication network.

l: the constant cost of the barrier synchronisation.

In real parallel architectures, the cost of a superstep is the sum of three parts: the cost of the longest parallel sub-superstep, the maximum time to deliver a message between two processers, and the cost of synchronisation [179]. Then, BSP uses the estimated cost of a superstep to estimate the cost of a program by summing the sub-costs of the remaining supersteps. Several updates have been made to the BSP cost model for different aspects. D-BSP [78], Decomposable-BSP, model is a variant that supports submachine synchronisation. Another variant is E-BSP [132], Extended BSP, which models that targets data locality and different patterns of communications. Recently, an updated BSP model, MultiBSP model, has been introduced by Valiant [222]. This model takes into account the memory/cache hierarchies and the memory/cache sizes on multi-core architectures.

In general, LogP and BSP models deal with communication bandwidth and network latency via their parameters [31]. In addition, both assume that processors can work asynchronously. But, the LogP model is capable of modelling the communication overhead and therefore makes LogP more realistic than BSP.

2.3.2.4 DRUM Cost Models

DRUM [96], Dynamic Resource Utilisation Model, is a resource-aware model that provides dynamic load balancing on parallel clusters with heterogeneous resources. This model contains information about the underling hardware resources and the interconnection network. Also, DRUM facilitates monitoring the capabilities of processing, memory, and communications for evaluation purposes.

Heterogeneity and scalability are the most important features covered in DRUM. Heterogeneous clusters are cost-effective platforms where their computational powers are able to be expanded through incorporating new additional nodes. In DRUM, each node n is assigned with a value, power, that represents the total load that can be given based on its processing and communication capabilities. Thus, the power of node is the weighted sum of processing power and communication power.

$$power_n = w_n^{comm} c_n + w_n^{cpu} p_n, w_n^{comm} + w_n^{cpu} = 1$$

Where:

$power_n$: the power of node n.

p_n: the processing power p_n.

c_n: the communication power c_n.

w_n^{cpu}: weight factor of processing capabilities of node n.

w_n^{comm}: weight factor of communications capabilities of node n.

2.3.2.5 System-Oriented Cost Models

Software-oriented cost models can be used to capture characteristics of parallel hardware through providing information about the cost of running concrete operations on specific machines [219], for example the cost of creating a thread. These sorts of models are often used in hardware design analysis of algorithms in order to provide further information during runtime. This provides significant information that may help in taking accurate decisions in dynamic resource mechanisms: load balancing, data locality, or scheduling.

2.3.2.6 Skeleton Cost Models

Algorithmic skeletons involve the parallel process, communication and synchronisation, and cost complexity [50]. Cost models are used to calculate the skeleton's cost complexity. The cost models of algorithmic skeletons measure the computation cost and communication cost for skeletons.

Darlington

There are many parallel implementations of skeletons, such as FARM, PIPE and (DC) Divide and Conquer. The cost model for each one according to Darlington is [76]:

- DC Skeleton: The implementation of a DC skeleton assumes that there are processors organised as a balanced binary tree, and all processors will work as leaf. The execution time can be estimated using the formula:

$$t_{sol_x} = \sum_{i=0}^{log(p)-1}(t_{div_{x/2^i}} + t_{setup_{x/2^i}+t_{comb}{}_{x/2^i}} + t_{comm_{x/2^i}}) + t_{seq_{x/2^{logp}}}$$

  Where

  t_{sol_x}: The time to solve a problem of size x.

  t_{div_x}: The time to divide a problem of size x.

  t_{comb_x}: The time to combine two results.

  t_{setup_x} & t_{comm_x}: The setup and transmission time for communication.

  t_{seq_x}: The time to solve problem of size x sequentially.

- FARM Skeleton: The implementation of a Farm skeleton has two major parts: the master processor and worker processors. The execution time can be estimated using the formula:

$$t_{farm} = t_s + R(t_e + 2t_c)$$

  Where:

  t_s: The start-up time.

  R: The number of tasks.

t_e: The time to solve one task.

t_c: The communication time.

- PIPE Skeleton: The execution time can be estimated using the formula:

$$t_{Pipe} = t_s + (t_e v + t_c)(p + n - 1)$$

where:

t_s: The start-up time.

p: The number of stages.

n: The number of elements in the list.

t_e: The execution time of one stage for one element.

t_c: The communication time between stages.

v: The number of virtual stages allocated to a real stage.

BSP

The restricted parallel programming model, BSP, is associated with algorithmic skeletal programming where the BSP approach eases optimising the performance of skeletal-based programs. Zavanella [237] has proposed a BSP-based methodology, Skel-BSP, that supports performance adaptivity for skeletons. Skel-BSP, which is a subset of P3L [73], uses an extension of the D-BSP cost model called EdD-BSP model. Enhancing portability in Skel-BSP is performed through adapting the structure of the program to the target machine using EdD-BSP parameters and implementation templates. Another example of a BSP-based approach is BSML [106], Bulk-Synchronous Parallel ML. BSML, which is an extension of ML, a functional parallel language designed for implementing BSP algorithms. Using BSML, efficient hardware can be chosen based on the prediction of performance of a BSP program on a given architecture. BSML is produced as a library [153] in the OCaml language [148].

BMF

Many researchers have presented cost models that support programs written with the BMF programming model. Cai and Skillicorn [204] have investigated PRAM cost models for BMF programs with list data structures. In this models, the cost of operation on elements are provided as well as the size of data structure. Much work to provide BMF-based programs with cost models can be found in [129, 117, 34].

P3L

P3L can use a LogP-based variant to predict the performance of program on parallel architectures. The P3L template-based compiler optimises the program to the target hardware using a cost model. This model provides more information than the basic LogP model does, such as processor speed and communication bandwidth.

An analytical model has been introduced in [180] where the computation time T of granularity k is:

$$T(k) = k(T_{dis}() + T_c \prod_{i=1}^{N} d_i + T_{col})$$

Where

T_c: sequential computation time.

d_i: data granularity for dimension i.

T_{dis}: data distribution time.

T_{col}: time for collecting results.

HOPP

The HOPP cost model [204] gives the cost of the potential implementation for a program on a target distributed-memory system. In HOPP, the cost of a program is calculated for n steps. C_{pi} is the cost of the functions in step i based the sequential implementation and number of processors. $C_{i,i+1}$ is the cost of communication between two consecutive steps.

$$\sum_{i=1}^{i=n} C_{pi} + \sum_{i=0}^{i=n-1} C_{i,i+1}$$

SkelML

SkelML [44] provides performance cost models for several skeleton, such as farm and pipeline. The SkelML compiler uses performance models to decide the efficient parallelism based on the predicted computational time and the network communication overhead.

Other

Other performance cost models have been developed for several languages. Hammond et al. [114] built a variety of cost formulas for a library of skeleton implementations in Eden, a parallel functional language. Thus, the proper implementation will be chosen at compile time through instantiating parameters of a given platform. Yaikhom et al.[234] presented a set of skeletons where each is associated with a cost model. These models use a process algebra approach and have some parameters that can be deduced from running of benchmarks.

2.4 Scheduling

One of the biggest issues in parallel and distributed systems is developing techniques for scheduling the tasks on multiple locations [54]. The problem is how to distribute the computations amongst all available processing elements to minimise the total execution time and increase the performance.

Within a parallel computing environment, computation, data, and network resources are shared amongst both system and application components. Consequently, a scheduler is needed to achieve better performance [102]. Schedulers are classified into three classes based on their performance goals. These are: *job schedulers* that enhance the system performance by optimising throughput, *resource schedulers* that control the resource usage in order to utilise resources or fair scheduling, and *application schedulers* that improve the performance of an application through optimising specific performance measures, like total execution time. Both job schedulers and resource schedulers promote system performance while application schedulers target

individual applications. Application schedulers are also referred as high-performance schedulers.

In this thesis, our target is reducing the total execution time for a parallel application so we will only review the developing of application schedulers, while resource and job scheduler are beyond the scope of thesis.

2.4.1 Scheduling Model

Parallel applications are composed of one or more tasks that need to be executed over different resources [103]. These tasks may communicate with each other to solve a particular problem. Scheduling these tasks on participating resources includes a set of operations to produce a schedule and a cost model for evaluating the performance measures. Scheduling involves the following activities: resource discovery, task placement, data mapping, and task/communications ordering. Hence, scheduling is assigning tasks and data into resources with some order in time.

High-performance schedulers use scheduling models to evaluate the performance, define a schedule, and perform actions to produce the resulting schedule. Using parameters from the application and the environment, high-performance schedulers perform the best schedule based on the schedule policy.

Developing an effective high-performance scheduler is challenging because of the heterogeneity of the hardware/software resources and the competition amongst users to acquire resources in a shared environment. However, the scheduling model used by a high-performance scheduler should represent the characteristics of the dynamic environment and the application performance. Hence, a scheduling model can: produce time frame-specific predictions because the performance varies over time; utilize dynamic information, which is needed to reflect the system state to develop resource-aware schedules; and adapt to chosen execution platforms for deriving accurate predictions.

A scheduling model comprises a scheduling policy, a program model, and a performance model.

A program model is an abstraction of a program using a data-flow-style program

graph or a set of characteristics. An example of systems that represent the program using a data-flow-style program graph is MARS [107]. In contrast, AppLeS [30] represents a program using a set of its characteristics.

A performance model evaluates the behaviour of the schedule. High-performance schedulers employ performance models to make an optimal schedule. A performance model is commonly parametrized with both static and dynamic information which can be provided by the programmer, system, or a combination. SPP(X) [23] is an example of a system that use performance models.

A scheduling policy is a set of rules that achieves a schedule to optimize the performance goal of the application. Applications may have different performance goals, where the common performance goal is minimising the execution time. As an example, Dome [20] focuses on minimising the execution time using load balancing as a scheduling policy. Much effort is on heuristic-based that are static schedulers and take decision based on assumptions from prior knowledge of benchmark execution [45].

2.4.2 Challenges of Application Scheduling

There are number of challenges that need to be considered for High-performance scheduling [103]:

- *Portability and Performance*: The main goal of scheduling is to improve the performance. But, having better performance depends on leveraging environment features. However, a scheduling strategy should balance the performance gain and the heterogeneity of the architecture resources.

- *Scalability*: it is important for a high-performance scheduler to use a dynamic, scalable mechanism to select the resources.

- *Efficiency*: a high-performance scheduler is predicting the behaviour and making a decision to redistribute the load. These decisions need to be accurate and the schedule to be efficient with low overhead.

- *Multi-scheduling*: resource schedulers, job schedulers and application schedulers are all working for their performance goals. Coordinating multiple schedulers is difficult and presents a challenge to the developers of schedulers. One common problem that may occur is thrashing which cause unstable load balancing. However, multi-scheduling strategies must consider the stability of the system for meeting their objectives.

- *Locality*: data locality may be affected when the tasks that process these data are moved. Scheduler developers should find a compromise between communication overhead and the desired performance goal [225].

2.4.3 Load Management

Load management is one branch of a family of global scheduling polices, for manageing the load of all locations in a network, cluster or Grid. The main goal of load management is to improve the performance of an application by evenly assigning tasks to each processing unit [177]. Load management is categorised into two types: static and dynamic.

2.4.3.1 Static and Dynamic Load Management

The aim of static load management is to minimize the execution time of an application [201]. Static load management predicts the run-time behaviour of a program at compile time by estimating the task's execution time and communication delays. The main advantage of predicting the behaviour of the application is that the overhead of the scheduling process takes place at compile time. However, the run-time of the application may have unpredictable conditions such as network delays or reliance on inputs, so that predicting the behaviour at compile time will be inaccurate and may not be equal to real values at run-time. As a result, static load management may make inappropriate decisions.

Dynamic load management depends on information collected at run-time to reschedule tasks from heavily loaded machines to lightly loaded machines. The aim of dynamic load management is to maximise the utilisation of processing power.

The advantage of dynamic load management over static load management is that the system does not need to be aware of the run-time behaviour of the applications before execution. Dynamic load management incurs a run-time overhead resulting from the communication cost of load information, the processing cost of decision making and the communication cost for task transfer.

There are four policies, which also can be polices for dynamic scheduling, for dynamic load management algorithms [92, 80, 172]. These policies are:

- *Information Policy* determines the information needed for predicting the behaviour in order to make a decision to redistribute the load. An information policy also specifies the mechanism to collect and diffuse the information that reflects the system state amongst locations. Triggering the collection of information can occur via many approaches. A location can ask for the state of other locations when it becomes a sender or receiver; this is called a Demand-driven approach. Or a location may share its state when it is changed; this is called a State-changed driven approach. Another approach is Periodic where collecting the information happens periodically.

- *Transfer Policy* indicates the condition to transfer the load from a heavily loaded location to lightly loaded locations. This policy may be a threshold-based approach, a relative-load approach, or a hybrid approach.

- *Selection Policy* decides the tasks that should be moved. There are two approaches in selecting the tasks: non-pre-emptive and pre-emptive. A non-pre-emptive approach assigns the tasks to the selected location before the execution of the tasks. By contrast, a pre-emptive approach relocates tasks to the selected location during the run-time. A pre-emptive policy can migrate running tasks and therefore it is yielding significant performance benefits. A pre-emptive policy is more costly than a non-pre-emptive policy, but it is more flexible.

- *Placement Policy* identifies the locations to which a task should be transferred. The commonly used approach is polling, by asking the destination location to

accept transferring the task. Selecting a location can be: random, which selects a random location to move the task; shortest, which determines the lightly loaded location as a destination; or threshold, where the selected node will be checked before moving the task.

In a dynamic load management system, the selection and placement policies are combined together to produce an optimised schedule or to balance the system load [151]. This combination can be either a push policy or a pull policy.

- *Pull Policy*: This is sometimes called a receiver-initiated policy, passive load distribution policy, or work stealing. In this policy, when nodes become idle, they request or steal work from other nodes.

- *Push Policy*: This is sometimes called sender-initiated policy, active load distribution policy, or work distribution. In this policy, the loaded nodes look for lightly loaded nodes to give them some work.

For a low system load, the push policy works well and minimises the overhead but this may cause unstable load in the system. On the other hand, a pull policy is better for high system load.

Examples of dynamic load management systems are Load Sharing Facility (LSF) [2] and GrapevineLB [165].

2.4.3.2 Strategies of Dynamic Load Management

Dynamic load management strategies are classified according to entities that hold the information and share the load amongst the resources. Thus, a dynamic load management strategy can be centralised, decentralised, or hierarchical [240, 186].

In a centralised management system, there is a central node which collects information about the system state and builds an estimate of the system state. The central node may hold a shared file which records updates from all nodes. The advantage of centralised load management is that the overhead is low during the estimation process. The disadvantages are poor scalability and failure-proneness.

In a decentralised management system, each node is responsible for collecting state information and constructing an estimate of the system state. This organization is not easy to scale to large system because it can incur large overheads to gain accurate and consistent state information.

In hierarchical management systems, both centralised and decentralised load management strategies are combined to inherit the properties and extract the advantages of both. A hybrid strategy can be implemented when nodes are divided into clusters and the data are exchanged amongst them.

2.5 Mobility

The term mobility refers to a change of location achieved by system entities [37]. In mobile computing, computations are moved amongst network locations and hence enable a better use of resources in a network [176, 187]. A mobile program is able to move its code and state from one location to another in a network and resume its execution [143]. Mobility has different forms: hardware and software mobility.

Hardware mobility means the mobility of devices, such as laptops and PDAs. Therefore, software mobility refers to moving computations from one location to another [80, 40]. Some classifications of software mobility are process migration and mobile languages. In process migration, the system decides when and where to move, while in mobile languages, the system gives the programmer the ability to decide the placement of computations on anew network location. MOSIX [25] is an example of a distributed operating system that supports process migration. An example of a mobile programming language is Java Voyager [3].

Check-pointing is a snapshot of the state of application; it is the main operation in mobile systems to move the computations amongst processors in a network or cluster [116]. Check-pointing is performed at a source location, sent and resumed at the destination location. Check-pointing can be performed on an individual process or on a whole operating system process. Check-pointing may be relevant to other states, such as opened files or shared memory so that the check-pointing at process level will often fail while the check-pointing at system-level will be able to get all

local states.

2.5.1 Mobility Models

Mobility can be performed at different levels of granularity [116]. These models are:

- *Data Mobility*: A simple approach to mobility is that the application can save its state and resume work from the saved point. Data mobility happens by moving the saved state between locations on a network.

- *Object Mobility*: An object is a single unit that includes code and data. Object mobility is serializing objects between machines where the program may contain several objects roaming between machines. For example, RMI (Remote Method Invocation) [184] will forward the calls transparently to the remote object when method invocations happen for that object. RMI has a global registry to save locations of a remote object during its life. Object mobility is more complex because the remote object has one or more threads running and these threads keep parts of the state of the object in the stack and CPU registers. Some object mobility systems allow mobility when the invocation reaches a specific execution safe point. For example, Emerald [131] supports object mobility at several levels of granularity [105].

- *Process Migration*: process migration is moving the state of a program and its data. The process is independent of the implementation language. Process migration faces a problem when a process leaves an open file or similar unresolved state in the originating host; this is known as residual dependency. One solution is to create a proxy process on the operating system on the originating host, and that process handles the access to the local process. This solution will require access to the resources over the network, so performance may be reduced, and the process may fail if one of the two hosts crashes, which may weaken the stability. Two examples of operating systems that support process migration are Sprite [88] and MOSIX [25].

- *Virtual Machine Migration*: A common problem with virtual machines is increasing hardware utilization [26]. This problem can be solved by relocating the workloads from an original host to another host before server downtime. This process is called Virtual Machine Migration and happens when the downtime of the server is planned or predicted. Sometimes VM migration happens with migrating disk state. All applications running in the VM of the original host will move to the new host. The shared memory and file system problems are solved in this type of migration. An example of virtual machine migration platforms is VMotion [1] which is included in VMware vSphere. This platform seamlessly enables moving live VMs between physical machines.

Data mobility is an example of a fine-grained technique. On the other hand, process migration and object migration are course-grained techniques. Virtual machine migration is the most coarse-grained type of mobility.

2.5.2 Properties of Mobile Systems

Mobile systems should have mechanisms to effectively use the available resources. The properties of mobile system include [80, 40, 105]:

- *Mobility Control*: A mobile system should have a mechanism to make the programmer able to decide on the mobile operation.

- *Weak or Strong Mobility*: Mobility has two forms defined by Fuggutta et el [105]: weak mobility and strong mobility. Weak mobility is moving the code from one location to another. Whilst, strong mobility moves the code and state information from one location to another and resumes the execution from the stop state [81]. Strong mobility is also known as transparent migration. Mobility systems may support weak mobility such as Java Voyager [3] or weak and strong mobility like JavaGoX [196].

- *Implicit or explicit mobility*: Implicit mobile systems move the active computations, like a thread, from one location to another in the network. Implicit mobile systems usually operate on a small scale, e.g. LAN or cluster [169].

However, in explicit mobile systems, the moving of active computations is controlled by the programmer. Explicit mobile systems usually operate on open systems and in large-scale settings [40].

- *Awareness of Location*: after execution, the program may need to access resources not located in the same location. In this case, the mobile operation will happen under programmer control and be related to the resources [52].

- *Safety and Security*: Mobile systems have been developed to work in a network where the resources are shared amongst entities of the network. Safety means preventing undesired behaviour of programs. Security means the integrity of the information and protection from malicious attacks [142].

- *Architecture Independent*: The main idea for mobile systems is to move the live computations between locations on large distributed systems. These locations may have different architectures and operating systems. Thus, it is necessary to compile the program into architecture-independent code that is able to work on heterogeneous networks [229].

2.5.3 Advantages of Mobility

Some of the main advantages of mobile computations are [211, 131]:

- *Load Sharing*: Moving the computations amongst processors on a network or system can lead to a better use of resources and lighten the load on slowly-used processors, and it gives a faster performance.

- *Communications Performance*: Moving the active objects that interact intensively to the same node can reduce the communication costs of their interactions.

- *Availability*: Moving objects to different nodes can improve service and protect against broken or lost connection.

- *Resource Utilisation*: An object visiting a node can take advantage of services or capabilities at that location.

2.5.4 Code Mobility

In traditional computing, each computation is linked to a single machine [105]. Thus, the code of the computations belongs to the local machine. This is not true for mobile systems. In mobile systems, the code, the execution state and the data of computation, can be moved to a different machine.

Mobile systems provide mechanisms that support weak or strong mobility. There are two mechanisms that support strong mobility: migration and remote cloning [216]. The migration mechanism pauses the computation, moves it to the destination machine, and resumes execution. When the destination machine and the time for migration are determined by the migrating machine, such migration is called proactive. In contrast, when the movement is determined by a different computation that has some relationship with the computation to be migrated, this is called reactive. For example, the MoviLog [242] platform supports migrating its computations either proactively or reactively.

The remote cloning mechanism will create a copy of a computation at a destination machine without detaching it from the current machine. Remote cloning can also be proactive and reactive [28].

Weak mobility is supported by a mechanism that is able to move the code amongst machines and either links it to a running computation or uses it as a code segment for a new computation [105]. The migration can be stand-alone code or a code fragment. The stand-alone code will create a new computation on the destination machine, whereas a code fragment will be linked and executed in the context of running code. The mechanism supporting weak mobility can be synchronous or asynchronous depending on the computation suspension relative to when the code is executed on the destination machine. The asynchronous mechanism can be in immediate or deferred mode depending on the execution of the code on the destination machine.

2.5.5 Agent-based Systems

An agent is computer software hosted in an environment [217]. Agents are designed to solve a specific problem in the system where they are located. The state and the behaviour of agents may change due to interactions with the environment either responding to external events or initiating actions in order to achieve particular objectives. Thus, agents have to be both proactive and reactive [130]. Systems that rely on agents as the key abstraction are called agent-based systems. Such systems may use a single agent or multiple agents that cooperate with each other to achieve a general objective. These systems are also known as multi-agent systems [231].

Properties that characterise agents are [231, 214]:

- *Autonomy*: each agent has control over its internal state without any external intervention. This state can be used to make the decision to perform some actions. Because of the autonomy property, agents are referred to as autonomous agents.
- *Reactivity*: agents situated in an environment respond with an action that may change the environment.
- *Pro-activeness*: agents learn from the environment and interaction with others to initiate goal-directed actions when necessary.
- *Sociability*: agents are capable of communicating with other agents or the environment to achieve a certain goal.

Much work on agents can be found in [230, 231, 195].

Agents also may have a mobility property that enables them to change their environment and move to another one [143]. Those agents are called mobile agents. Agents that do not have the mobility property are called stationary agents. To gain information from remote systems, a special communication mechanism is supported in stationary agents. However, mobile agents are free to move amongst systems as they are not bound to a particular system. Indeed, mobile agents keep their state and code while moving which enables them to resume execution on other systems.

Furthermore, mobility gives the agents the facilities needed to be in the same host with the resources they request and the objects with which they interact. System performance can be improved by agent mobility through reducing the network load and overcoming network latency.

Mobile agents provide the flexibility and abstraction needed for building distributed systems.

2.5.6 Autonomic Systems

Autonomic systems are capable of managing themselves to achieve high-level objectives given from an administrator [139, 171]. Autonomous systems are also referred to as autonomic systems. In this context, autonomic systems are self-management systems that can maintain and manage their operations in the case of system changes, such as workload, demand, or components, and software/hardware failures. Self-management autonomic computing systems may have one or more of these aspects [171]:

- *Self-configuration*: an autonomic system is able to automatically configure, adjust, setup, and install components. All system configurations will be adapted in accordance with administrator objectives.

- *Self-optimisation*: autonomic systems attempt to improve their efficiency by endeavouring to perform operations with high throughput and achieve goals at optimum levels. Self-optimisation systems monitor their state and take decisions, such as resource allocation, to improve the performance.

- *Self-healing*: autonomic systems are able to adjust, diagnose, and repair localised problems and failure in the software and hardware.

- *Self-protection*: the system can protect itself from malicious attacks. Also, the system can use early reports to expect and prevent problems by taking actions to avoid failure.

An example of an autonomous system is ASP [4] (Autonomic Job Scheduling Policy) for Grid that supports three of the self-management aspects: self-optimisation,

self-healing, and self-protection. Liu et el [150] have presented a component-based programming framework which is an example of a self-configuration system. Moreover, Deng [80] has developed resource-aware programs with a self-optimisation ability. These programs are called AMPs (Autonomous Mobility Programs).

2.6 Summary

A cluster is a distributed memory system that uses message passing approach for communication. Emerging the latest multi-core technologies in the cluster systems offered many benefits. System developers are forced to deal with parallelism across nodes, cores and other processing units. It becomes necessary to make the application scalable and automatically adaptable to different number of nodes/cores. In this thesis, we target multi-core cluster with diverse number of nodes and quantity of processing elements. To match our objectives, we need to design a distributed programming framework which is able to exploit multicore clusters. We use MPI as a message passing library in the distributed memory architecture to secure the communications amongst those components. Our framework is designed as Master/-Worker model to maintain the cooperation in the framework. At the node level, we use Fork/Join pattern to manage the coordination inside the workers. Accordingly, we use the PThread library to flexibly manage the threads within the multicore nodes. At the level of the problem, or most specifically, the task, each task uses SPMD model. The GPU programming is beyond the scope of our thesis where we concentrate on the compute power of the CPU cores of the node.

This framework is implemented using skeletal approach and hence it offers a high level data-parallel skeleton. This skeleton separates the computation from the coordination. Hence, this skeleton helps in optimising the problems through improving the productivity of programmers by focusing on the domain-specific issues while parallel and communication details are implicitly maintained.

The skeleton implementation mainly supports executing farm pattern problems but it also can be used to solve problems such as pipe pattern or map-reduce pattern problems. Other patterns such as divide and conquer and scan patterns are not

implemented in our framework. Skeletons usually provided as a language extension, library or parallel programming language. A survey of skeletons has been proposed in the literature. This work proposes a skeleton as a library in the C programming language.

To enhance the dynamicity and adaptivity of our skeleton, we develop a high performance dynamic application scheduler to optimise the performance of the skeleton. The main goal of the scheduler is minimising the total execution time under loaded conditions. This scheduler uses real time observations and performs a set of event-based operations to enhance the skeleton performance goal. Moreover, the skeleton scheduler is triggered by the loaded nodes. Hence, push policy has been used to implement the selection and placement policies. Our scheduler follows a hybrid centralised/decentralised approach to exploit advantages of both strategies. The operations of the skeleton scheduler depend on local coordination without interfering with other scheduling systems or the native operating system scheduler. There is a wide range of scheduling policies that has been proposed in the literature. However, schedulers target potential execution environments, language representations, and problem domains. As a result, schedulers are difficult to compare [141].

The skeleton scheduler takes decisions based on a dynamic performance cost model. This cost model helps the scheduler to decide if the current tasks can run faster on remote locations taking into consideration the changeable load, the running architecture and the progress of the executing problem. Therefore, this cost model depends on measurements at run-time. This cost model is based on the model developed by Deng [81, 80] where our new version supports multicore architectures and takes into account the external load of the application in the executing environment. Skeletons that are guided by performance model are also proposed in many works. Examples of these skeletons can be found in [80, 51, 223, 9, 29].

This scheduler uses mobility in transferring live computations from node to node using a pre-emptive approach. This mobility is implemented at the application level, the skeleton, where strong mobility with data mobility has been used. In our skeleton, mobility operations occur transparently where mobility operation includes

saving the execution state, transferring, and resuming the execution of live computations. Some programming language supports mobility like JavaGoX [196] and Java Voyager [3] where some skeletons can get benefits of this feature like mobility skeletons [81, 89]. In such skeletons, common patterns of mobile computations are encapsulated. Other mobility support can be provided by the system like MOSIX [25] where MOSIX is cluster management system that manages resources, allocates, and migrates processes amongst nodes.

Chapter 3

Self-Mobile Skeleton

Skeletal programming has given significant benefits to developers to relieve them from the difficulties of parallelism and keep them focusing on solving problems. Such an approach has put forward solutions to exploit parallel systems without going into low-level details, such as communications and coordination. This work proposes a generic data-parallel skeleton, HWFarm, which can exploit multicore clusters. This skeleton is self-mobile where all mobility operations are implemented inside the skeleton. In this chapter, we start with the concepts of designing skeletal-based systems in Section 3.1. Then, we propose the design and the implementation of our skeleton with further details about its usability in Section 3.2. Next, we show experiments for evaluating the performance in Section 3.3. Cost modelling and scheduling will be discussed in the next chapters.

3.1 Pragmatic Manifesto

A wide range of skeletons are provided through either a library or language constructs. To effectively design skeletal-based systems, Cole [67] presented a manifesto. These principles are:

1. *Propagate the concept with minimal conceptual disruption*: this principle requires that the skeleton should be provided as a simple concept in an existing programming language. This is necessary to ease the difficulties in learning new programming languages with new constructs.

2. *Integrate ad-hoc parallelism*: the construction of skeletons must be integrated with structured parallelism. Hence, skeletal systems should be developed in order to implement a parallel pattern that has not been supported by available skeletons.

3. *Accommodate diversity*: the specification of a skeleton offers a level of flexibility that provides variations in implementation of the real algorithms. Beside flexibility, a straightforward abstraction of skeletons must be constructed. As a result, a balance is needed between simplicity of abstraction and realistic flexibility.

4. *Show the pay-back*: results and benefits of developing skeletal systems must be presented. We must also show the improvements offered by the adoption of skeletal systems.

Danelutto et al [72] extended Cole's principles by adding three related to reusability and modern heterogeneous platforms. These principles are:

5. *Support code reuse*: this allows the skeletons to be reused with very little change to the sequential code.

6. *Handle heterogeneity*: with various kinds of parallel architectures, the skeleton must be able to run on different platforms. This means that the implementation should be adapted to execute on heterogeneous resources such as clusters or Grids.

7. *Handle dynamicity*: skeletons may run on environments, such as non-dedicated clusters, that have changeable available resources. Hence, skeletons must be supported with mechanisms to handle such situations.

Now, we will explore our skeleton that meets these principles to be able to integrate with the mainstream of parallel programming.

3.2 HWFarm Skeleton

The *HWFarm* skeleton is the main body of our work in this thesis. Its name is a combination from the initials of Heriot-Watt University, *HW*, and the parallel model used to implement this skeleton, the Farm parallel programming model. *This skeleton has a built-in mobility feature which enhances its dynamicity. This enables the skeleton to reallocate its computations seeking for faster processing units. Thus, this reduces the executing time and improves the performance of the skeleton.* Unlike mobile skeletons that are based on mobile languages [89], the HWFarm skeleton is based on the C programming language [140] and depends on MPI [112, 206] and the PThreads [48] library.

In this section, we will explore the motivation and the design of the HWFarm skeleton. Next, we introduce the techniques used to develop the skeleton and propose the implementation of the skeleton. Then, we show how the skeleton can be used to parallelise a sequential program. Finally, we discuss how HWFarm met the skeleton design manifesto.

3.2.1 Motivation

Shared, non-dedicated environments offer conputing platforms for executing parallel applications. Sharing these resources raises new challenges in terms of the scheduling and management of applications demanding computational power. Resource contention is one of these challenges where processes of the user applications compete to acquire processing units. This contention has an influence on the performance of the running applications. Therefore, resource contention implicitly leads to poor performance and application slow down and latency [199, 238].

Figure 3.1 shows a motivating example of the influence of external workload. This test program estimates Pi using the Dart algorithm [22]. It is implemented using C and OpenMP where all threads cooperate to calculate the required value. We run the test program with other programs running concurrently as workload programs. These programs are EP and IS in NPB 3.3 (NASA Parallel Benchmark) [174]. The Dart program and the workload programs are tested on a machine with 8 cores. We

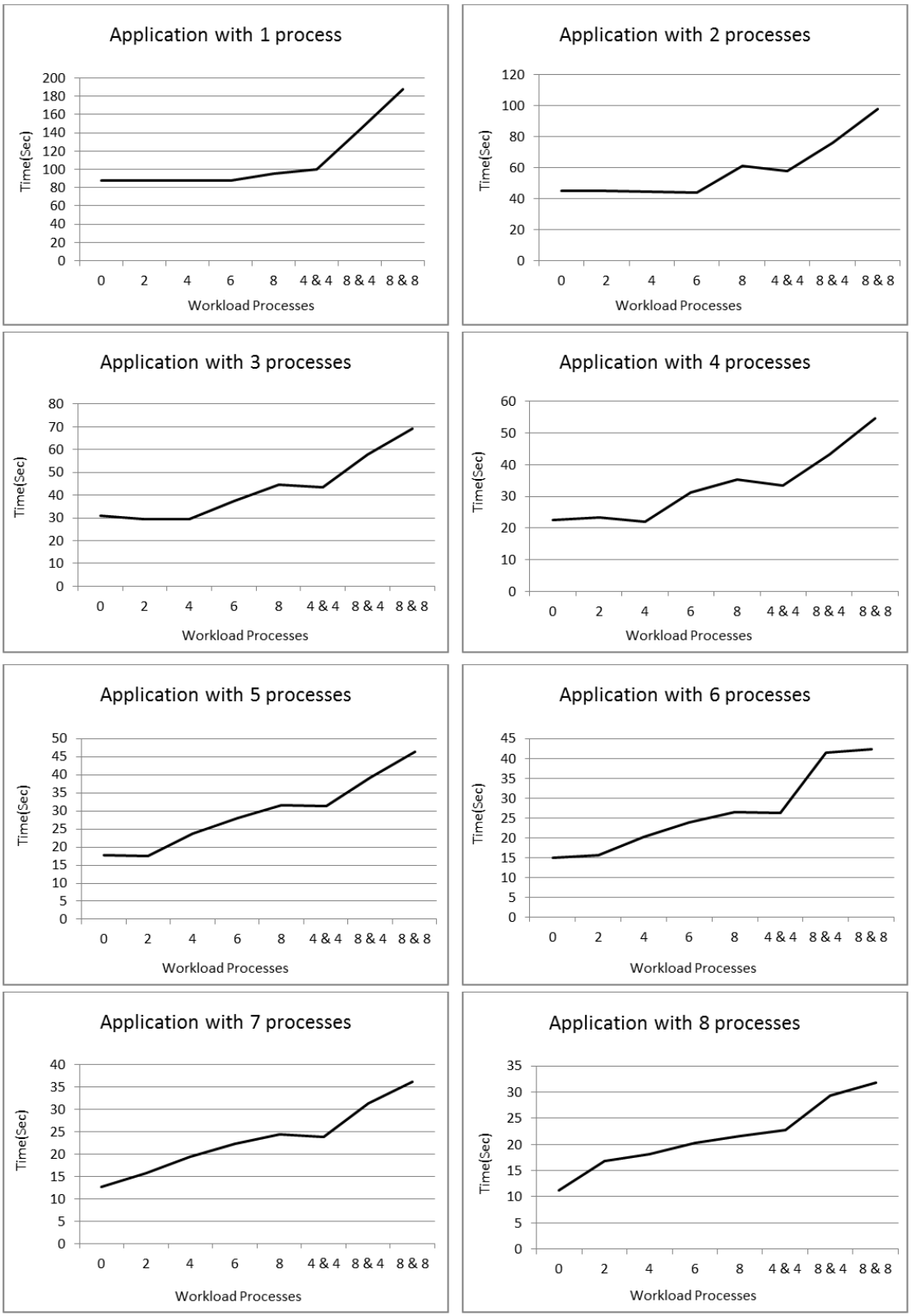


Figure 3.1: The effect of running multiple applications on the same processor.

repeated the experiments in different scenarios in order to check how applications affect each other. First, we ran the Dart program with no external workload and repeated the execution with different number of threads. Then, we simultaneously ran the workload program EP with 2, 4, 6, and 8 processes. Afterwards, we added more workload by running another workload program, IS. Therefore, in the last three scenarios, we ran 4 processes of EP with 4 processes of IS (4 & 4), 8 processes of EP with 4 processes of IS (8 & 4), and 8 processes of EP with 8 processes of IS (8 & 8).

In our example, the processes of the Dart program and the processes of the workload programs share the CPU where the local scheduler manages to assign a core to each process. But, if the total number of processes for all running applications on the machine exceeds the number of cores, the local scheduler will follow its policy to give a fair amount of time to each process requiring processing power. As a result, each process does not get the processing power needed and therefore the total execution time will increase which in turn leads to poor performance. This can be observed in Figure 1 where each sub-figure reflects the execution time of the Dart program running with other workload on the same machine.

To solve this issue, the execution of a parallel application needs to be dynamically adapted for optimising the performance goals, especially, when working in an open, shared, non-dedicated environment where the external workload is changeable and unpredictable. This thesis offers a mechanism to schedule and manage the local application load to avoid resource contention problem in shared computing platforms. The contention we address is the *computing power contention* where other contention such as memory and network contentions are beyond the scope of this work.

3.2.2 Skeleton Design

The aim of this work is to propose a high-level function developed using a skeletal-based approach, HWFarm. This skeleton takes into consideration the external workload through self-adaptiveness and therefore this will make the skeleton aware to

the environment workload. Based on the load state, the skeleton can reallocate its computations to other nodes in order to meet its performance goal, reducing the total execution time. In this sense, the HWFarm skeleton is self-optimised. The HWFarm load redistribution will diminish the influence on each other of multiple applications running on a machine. Hence, the performance of all applications (our skeleton and other programs) should be significantly improved, see Chapter 7.

We initially developed a skeleton [167] that executes the user program in parallel. This skeleton is supported with a simple cost model that deals with internal and external load. This skeleton assigns one task to each worker and transfers the task if the worker is highly loaded. We then extended our previous work to support multi-core architecture with costed scheduling decisions.

3.2.2.1 Static Skeleton

Here, we will discuss the main concepts in designing the HWFarm skeleton. Figure 3.2 shows the basic structure of the HWFarm skeleton.

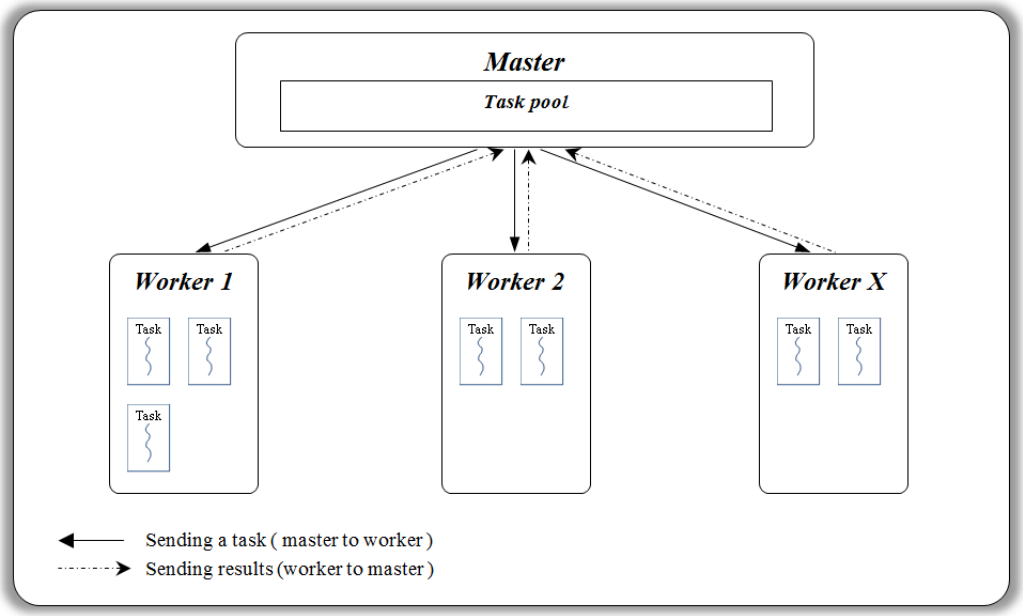


Figure 3.2: The HWFarm structure.

Coordination Pattern

The coordination pattern of the HWFarm skeleton is the farm parallel programming model [163]. In this model, we have two kinds of processes, master and worker. Using

the farm model, the running computations on remote workers can be monitored. Furthermore, this model helps in diffusing load information amongst the workers which is helpful to make accurate decisions. In our skeleton, we assume that the task pool is static and all tasks are assigned to workers and hence there are no new tasks waiting in the pool. One of the disadvantages of the Master/Worker model is a bottleneck due to the centralised master serving all workers. A bottleneck occurs when a worker must wait until other workers finish communicating with the master. This can be avoided through reducing the master-worker activities and devolving the critical making decisions to remote workers. Details of this hybrid mechanism are discussed in Chapter 5.

Master

The master is responsible for the whole coordination in the skeleton via: creating the tasks, computations; dividing the data; assigning the tasks to workers; and collecting the results of execution.

Worker

The worker executes the received tasks from the master and exchanges the load information with other workers and with the master. The model used in the workers is Fork/Join programming [163] where the worker maintains local threads and manages the communications with the master.

Task Model

Tasks in the HWFarm skeleton are intensive computations that process data and run concurrently in parallel. These tasks are initialised in the master process where each task is linked with a function and an evenly divided chunk of data. In workers, the function of the task will be executed to manipulate the input data to produce the output data. An important assumption in this model is that the lengths of all tasks are equal. In addition, another assumption is that there is no dependency or communication amongst the tasks so that they are fully independent equal-sized

tasks. The chunk size is set by the user and hence the length of the task and the number of tasks are not controlled by the skeleton.

Task Allocation

Assigning tasks to workers is based on the total number of cores and the number of tasks. The tasks will be distributed amongst workers based on a static allocation model used by the master. This distribution will achieve an initial balanced load in proportion to the number of cores on each worker. Details of this model are in Section 3.2.4.2.

Program Model

The class of problem that the skeleton executes is similar to the loop parallelism model [163]. In the HWFarm model, the program has a number of iterations to process a chunk of data. Hence, the program will perform the same operations on different data segments. Thus, the skeleton can be classified as a data-parallel skeleton.

Communication

Based on the coordination pattern, the communications inside the skeleton are only between the master and the workers. Therefore, the connections are a master-worker connection when the master assigns a task to the worker and a worker-master connection when the worker returns the results to the master.

Platform

One of our design principles is to tackle homogeneous clusters. As a result, the parallel computing architecture we target in the HWFarm skeleton is a multi-core architecture, in particular a multi-core cluster. Cluster nodes may have different number of cores with varied characteristics. In this thesis, GPU architectures and CPU accelerators are not addressed.

Result Collection

Once a worker completes the execution of its tasks, it will send the results to the master. Then, the master gathers the sub-results into a global array and delivers it to the user program. The user program can now deal with the processed data, like flushing to an external file or a disk.

3.2.2.2 Mobility Support

We provide our skeleton with ability to move running tasks amongst nodes in order to have an improved schedule in the system. We use data mobility granularity where the application itself is responsible for transferring the code, the data, and the state.

The HWFarm skeleton is built as an abstraction between the coordination and the program. But, to make the skeleton able to move running tasks, there is a need to access the user computations to monitor and manage their execution state. To achieve this goal, the skeleton needs to keep a reference to all data processed in the task as well as the running state. This requires that the user has the burden to separate the state of execution from other internal iterations. In the HWFarm program model, loop parallelism, if the variables that hold data are globalised out of the main loop, this will save the state of the execution. As an example, during running a loop, the progress of the execution can be indicated by the main counter. Thus, whenever this counter is checked, the progress will be known.

Execution state includes the main loop counter that increases while the function is running. Also, the state can include any variables that are needed for the computation.

Besides moving the state, mobility includes moving the results of the processed data. Thus, when the program resumes, the sub-results will be available, and the program will continue to produce the remaining results.

Mobility is triggered in the skeleton if it is better to execute selected tasks on faster locations. When the scheduler decides to move a task, the mobility operation will be triggered. First, the source worker requests permission to move a task to the destination worker. Once permission is received, the source worker implicitly

performs check-pointing which is an operation to pack the task data and its state before transferring the whole computation. Then, the selected task moves to the destination worker. As a result, we have a new connection between workers involved in the mobility operation. Accordingly, the connections in the skeletons are master-worker for allocating tasks, worker-master for sending results and worker-worker for mobility.

Figure 3.3 shows the structure of the HWFarm skeleton and how the master and the workers communicate with each other to execute the problem in parallel.

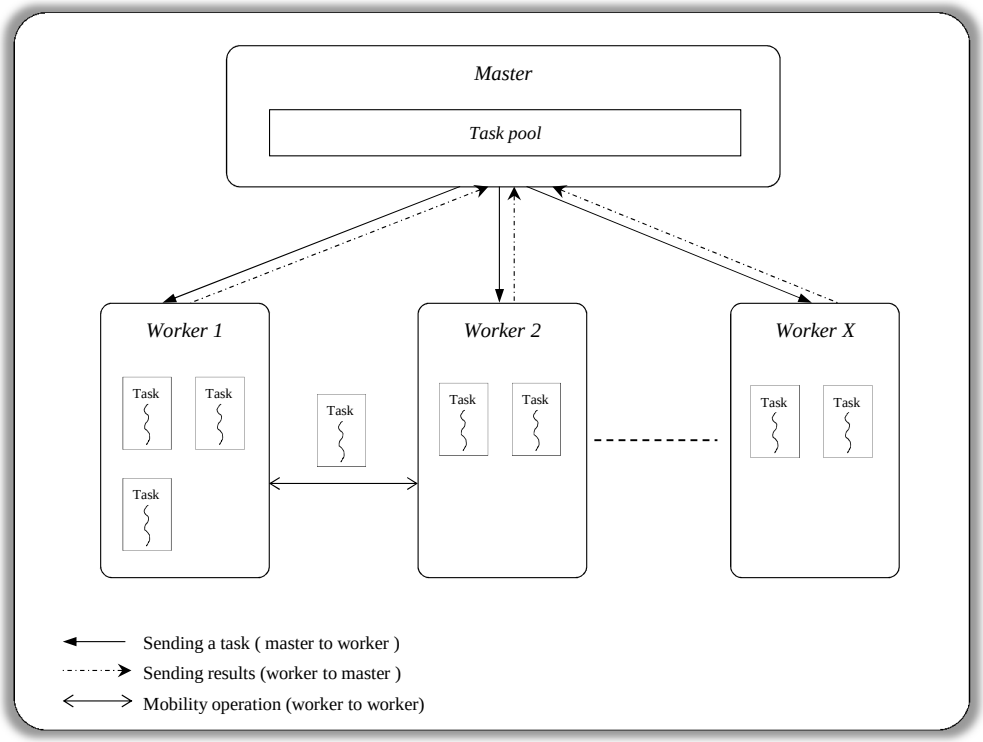


Figure 3.3: The HWFarm structure with mobility.

3.2.3 Host Language

Providing a high-level skeleton in a common existing language is much preferable to the programmer than learning a new programming language. The HWFarm skeleton is implemented in the C programming language, one of the most pervasive, dominant programming languages in software engineering. It has many features that are helpful in implementing our skeleton [140, 18]; some of them are:

- It is widely used in the software development domain.

- C uses memory through pointers which helps also in polymorphic programming (void pointers). This pointer capability has a significant use in supporting function pointers. This has many benefits for high-level programming such as abstraction.

- C gives access to the hardware and it is closely related to low-level languages such as Assembly.

- C is portable and not linked to any operating system or processor type. This enables our skeleton to run on a wide range of architectures.

To support parallel communications amongst the participating processes, we used the MPI model [206]. This model is widely used in multi-processor architectures. Thus, all aspects related to creating the processes and other issues are in MPI where process management is implicitly handled in the MPI communication library. The MPI library used in this work is MPICH.

To employ the shared memory platform, we used the PThreads library [48] that provides full control of creating, managing, starting, and killing running threads. OpenMP offers a mechanism to program shared memory but PThreads has full control in order to maintain multi-threaded programming.

3.2.4 Skeleton Implementation

HWFarm is a skeleton provided as a function call that hides low-level details from the user. In this section, we will explore how the skeleton deals with data. Then, we show the allocation model used by the HWFarm skeleton. Finally, we give a further look inside the structure of the skeleton.

3.2.4.1 Dealing with Data

In sequential programs, the program processes the input data to produce output data, but, in concurrent execution, the program may have multiple instances where each processes local data while all instances can access shared data. All instances work to produce the output data; see Figure 3.4.

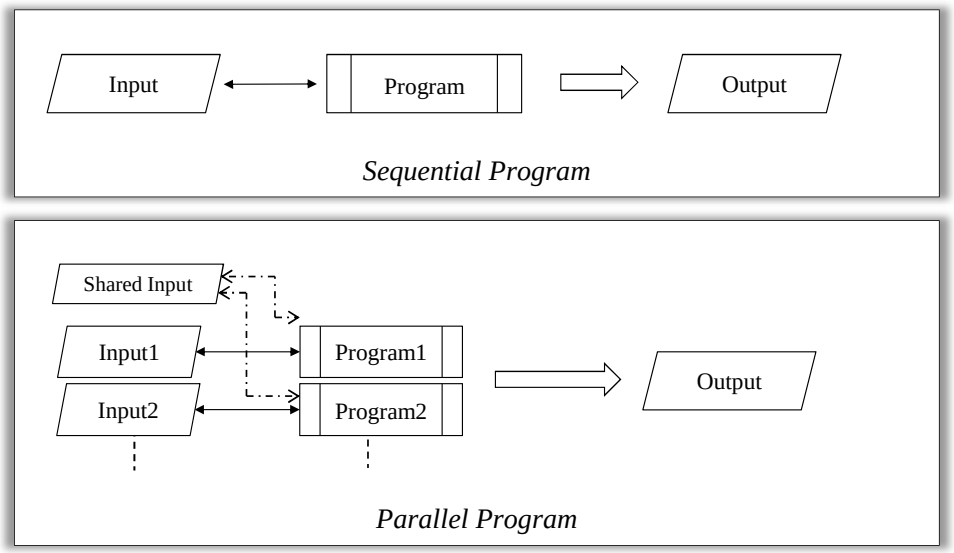


Figure 3.4: Sequential and parallel programs.

In the HWFarm skeleton, all tasks are running together. These tasks are distributed over the machines where some tasks may share the same node. To improve the flexibility of dealing with local and shared data in a node, the HWFarm skeleton classifies the data into three classes: input data, state data, and output data. All these data buffers are identified by the user. Input data is both shared and will be broadcast to all workers and local data will be equally divided into tasks. State data is configured and set by the user and based on the user-program to save the execution state of each task. Output data holds the results of the processed data; see Figure 3.5.

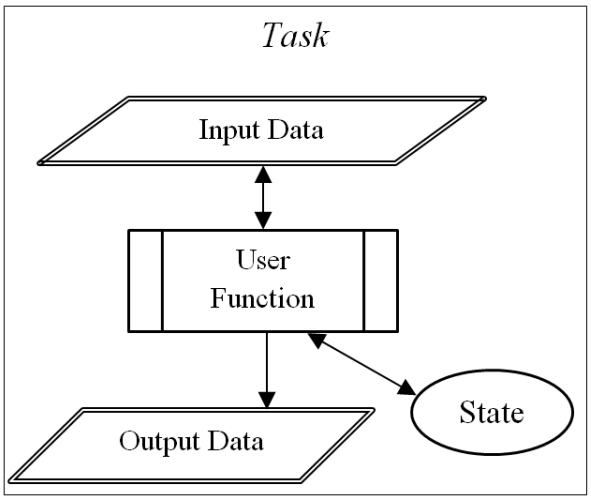


Figure 3.5: Task structure in the HWFarm skeleton.

Each task in the work pool has at least: a pointer to the user function, a pointer to the shared input data, a pointer to the local input data, a pointer to the execution state, and a pointer to the output data. All these pointers will be set dynamically inside the skeleton.

Data Configuration

To properly assign the data to tasks, it is a requirement that the whole data should be in consecutive memory locations. This is not the case when the memory allocation is dynamic. To solve this issue, especially when dealing with algorithms that are implemented using dynamic mechanisms, the user is restricted to keep the input, state, and output data in consecutive locations in the memory. This will avoid problems when assigning a task to a worker where the potential segment of data is selected. Also, this helps the skeleton to keep the data ready when a check-pointing is required.

Depending on the algorithm implementation, data buffers need to be set and allocated before the skeleton call. Each data buffer, except state, requires three parameters specified by the user: the buffer of the allocated data in the memory, the size of the memory location for one data item, and the length of the data allocated for one task. For example, if we have an array of 100 integer numbers and we want to create 10 tasks, the parameters for this user-array are:

$$data\_input : A; data\_input\_item\_size : 8; data\_input\_length : 10$$

where: A is the name of the input buffer; 8 refers to the size of one data input item; and 10 is the number of items in one task. In this example, $data\_input\_item\_size$ holds the value of 8 which is the number of bytes to store one integer value. Generally, this value depends on the data type of one item unit in the input buffer. Also, this value depends on the hardware on where the skeleton runs. As a result, to keep the skeleton hardware-independent, the user is required to dynamically assign the allocation size of the input item to properly maintain this data by the skeleton. Here, this value can be obtained from `sizeof(int)`.

The data type of the input buffer is not restricted to simple data types. The skeleton gives the user ability to define custom data types. But, the user is also required to provide the same details for the relevant structures. Then, *data_input_item_size* refers to the size of the data structure defined by the user. Yet, they have to make sure that all structures in the memory are consecutive.

State data is the main part of the data that saves the execution state. The state in HWFarm is defined in the `hwfarm_state` struct as follow:

```
typedef struct hwfarm_state{
    int counter;
    int max_counter;
    void* state_data;
    int state_len;
} hwfarm_state;
```

`hwfarm_state` struct has four elements: two for the counter/index of the main loop, a buffer for user defined state data, and the length of that buffer.

The user program must have a main index-based loop with a counter and the maximum iterations of this loop. This counter should be used to iterate through the data. These values will be set by the user before the skeleton call and then used by the user function as an input. `state_data` buffer is any data that the user may need before or during the task execution where `state_len` is the size of this buffer in bytes. The counter will be used later by the scheduler for the estimation and mobility operations. Hence, it is very important to configure the counter properly before the function call and inside the main loop of the user program. This may require minor re-factoring of the loop to be usable in the skeleton.

Figure 3.6 illustrates the work of the HWFarm skeleton from the perspective of data. In this example, the problem will be divided into 4 tasks so that the input data is divided into 4 chunks with a chunk per a task, see Figure 3.6.A. There are two workers and hence two tasks are allocated to each worker. Then, the master sends the shared data and the allocated tasks to the participating workers. Workers receive the tasks and start executing, see Figure 3.6.B. On each worker, tasks execute the

program on their local input data and may use the shared data. When all executions finish, the results of each task are ready to be sent to the master. The master gathers the results to produce the final output, see Figure 3.6.C.

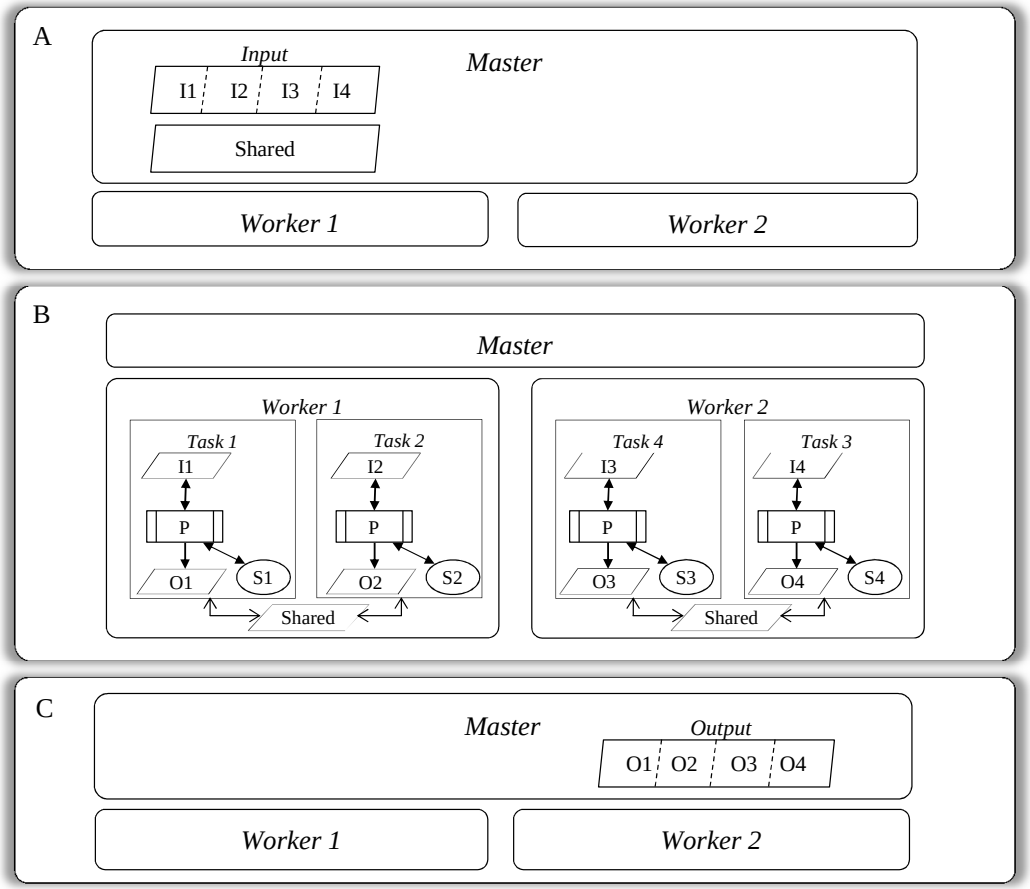


Figure 3.6: The distribution of data in the HWFarm skeleton.(I: Input, O: Output, S: State, P: Program).

Data Manipulation

The data will be delivered by the skeleton to the user-defined function through a `hwfarm_task_data` struct:

```
typedef struct hwfarm_task_data{
    int task_id;
    void* input_data;     int input_len;
    void* shared_data;    int shared_len;
    void* state_data;     int state_len;
    void* output_data;    int output_len;
```

```
    int* counter;          int* counter_max;
} hwfarm_task_data;
```

The fields of this structure are as follow:

- `task_id`: The id of the current task.
- `input_data`: The reference of the input buffer(chunk).
- `input_len`: The length of the input buffer.
- `shared_data`: The reference of the shared buffer.
- `shared_len`: The length of the shared buffer.
- `state_data`: The reference of the state buffer(chunk).
- `state_len`: The length of the state buffer.
- `output_data`: The reference of the output buffer.
- `output_len`: The length of the output buffer.
- `counter`: The reference of the main counter.
- `counter_max`: The reference of the maximum number of iterations in the main loop.

When the user function is called, all data related to the task will be available in this struct. The user has to follow the reference style in writing the code especially the counter. This will keep all changes accessed and controlled by the skeleton for enabling mobility and scheduling.

Inside the iterations of the main loop in the user program, the user can define any data type and use any allocation method. But, before reaching the end of the iteration, they have to save the result to output data and update the state. Updating the state includes updating the index value, shared values and any other data needed between iterations.

See the example in Section 3.3.2 that explains using the skeleton with its state.

3.2.4.2 Allocating Model

Exploiting a parallel platform requires having some knowledge about its architecture to effectively distribute the load for the best performance. Low-level details about the architecture and information about the executions are good metrics to achieve resource-aware schedule decisions where the initial schedule has a significant impact on the total performance.

A load balancing mechanism works well when all nodes have the same characteristics. But, in heterogeneous multi-core clusters, where each node has an arbitrary number of cores, such a mechanism may not work. To solve that, the HWFarm skeleton takes into account the heterogeneity of the participating nodes in order to achieve the best initial task distribution. However, HWFarm uses a simple static allocation model parameterised with the number of cores for each worker as well as the total number of tasks. This initial model ignores the communication costs and any dynamic metrics to reduce the overhead incurred at the skeleton start-up.

Suppose node i has C_i cores where the total number of nodes is N. Then, the total number of cores C is:

$$C = \sum_{i=1}^{N} C_i$$

When each worker is assigned to one node, the number of tasks allocated to each worker is:

$$T_i = \lceil \frac{C_i}{C} * T \rceil$$

where: T is the total number of tasks and T_i is the number of tasks allocated to worker i.

Figure 3.7 shows the number of tasks assigned to each worker for different node instances. In this distribution, the number of tasks allocated to each worker is the proportion of the number of cores in that node on which the worker runs.

3.2.4.3 Implementation Summary

The aim of the HWFarm skeleton is to execute sequential user code in parallel. Accordingly, the user should take into account that this code will be concurrently

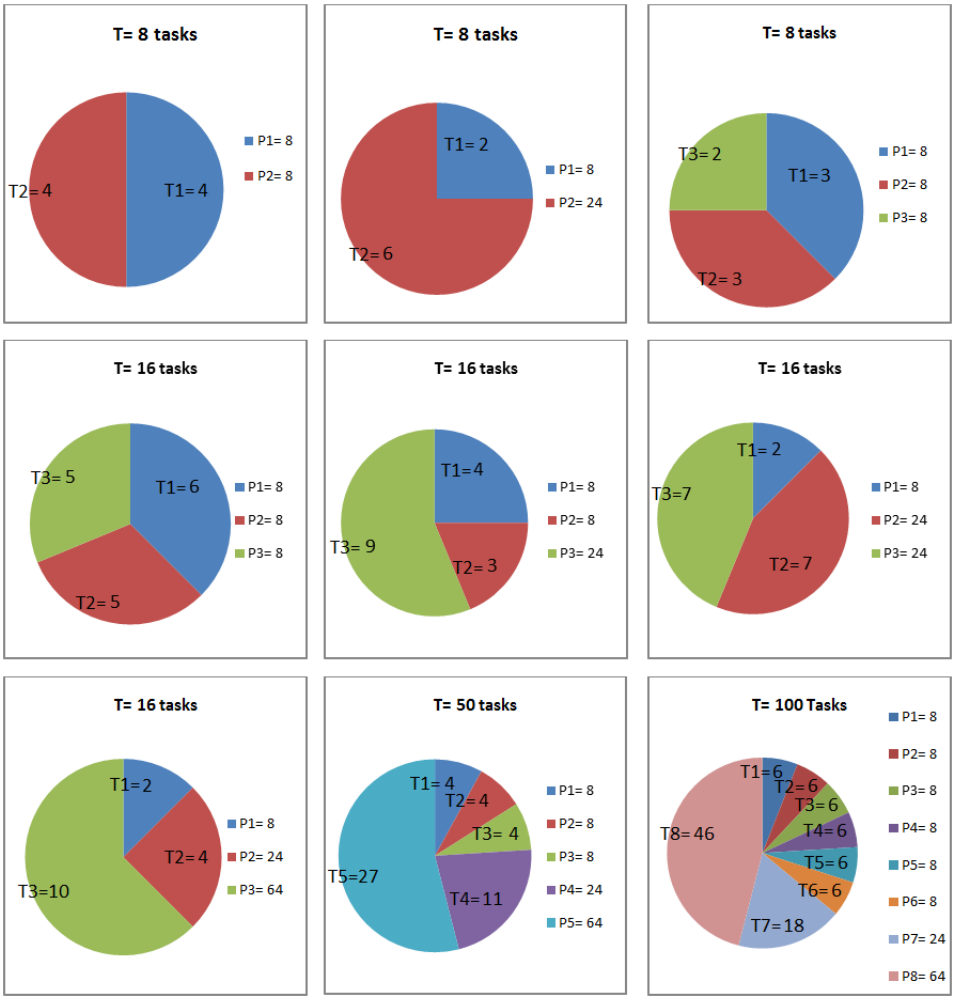


Figure 3.7: The distribution of tasks based on the allocation model. 8: 8-core node; 24: 24-core node; 64: 64-core node.

executed on chunks of data. After preparation of the code and data, the user can call the skeleton and wait for the results to handle the processed data. Now, we will explain the skeleton activities to accomplish the whole operation.

As outlined in Section 3.2.2.1, the coordination pattern used to implement the HWFarm skeleton is Master/Worker. Master and workers are MPI processes. These processes will be allocated to the resources according to the default MPI process manager.

The parallel system targeted by the skeleton is a multi-core cluster which is composed of a number of machines, nodes. Each node in this cluster has multi-core processor and a memory. Fig 3.8 shows the deployed HWFarm processes over the cluster's nodes. As a result, we have a master process allocated to one machine and worker processes allocated to other machines.

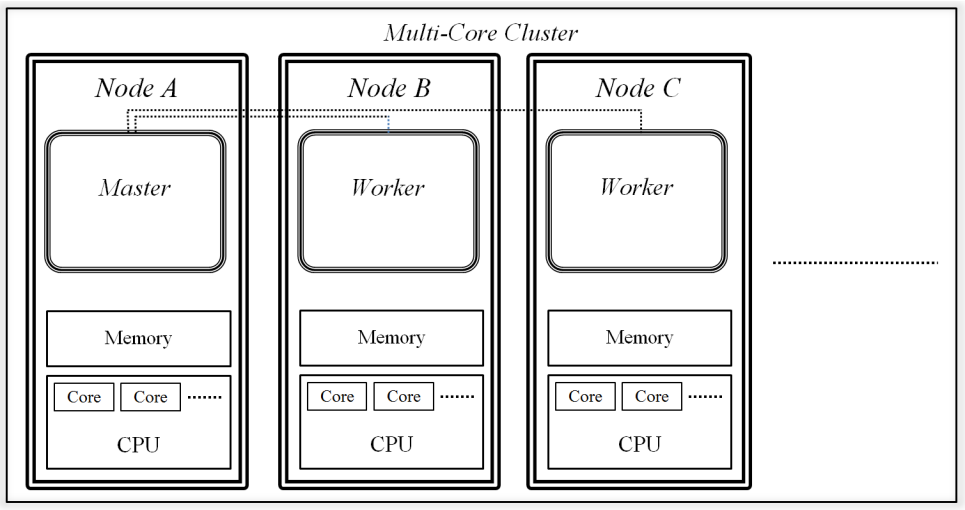


Figure 3.8: Allocating MPI processes into cluster nodes.

Master

The master process works as a global coordinator for the skeleton. The master starts by creating the pool of tasks based on user parameters and user data. Each task has data and a function. Then, it assigns a selected number of tasks to each worker based on an allocation model. Each worker may execute one or more tasks. Finally, when a worker finishes executing a task, the master will be ready to receive its results and gather all sub-results to be delivered to the user program; see Figure 3.9.

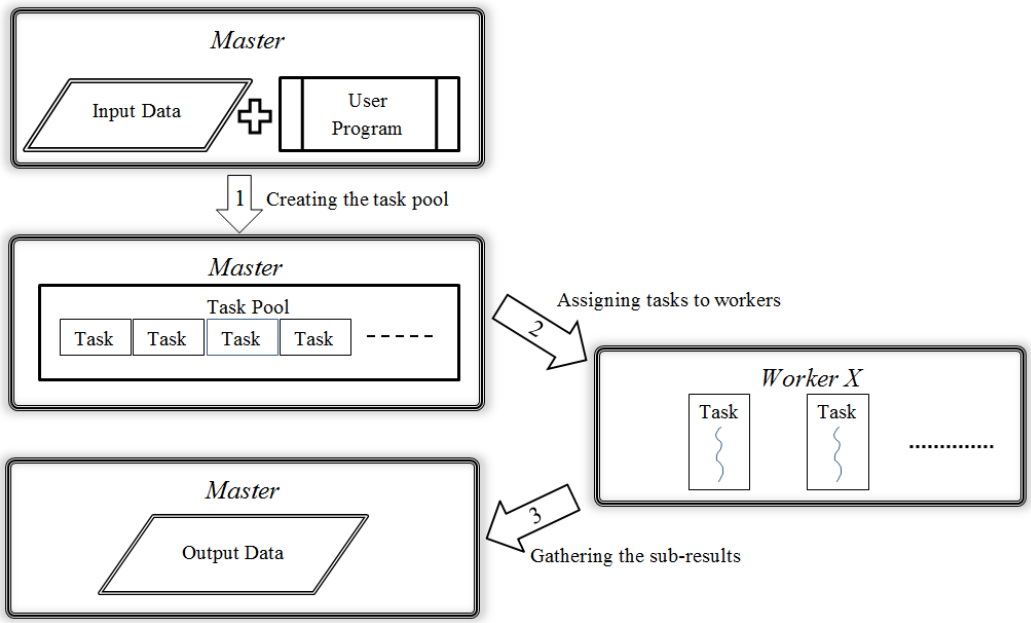


Figure 3.9: Master/Worker cooperation.

A task in HWFarm has many details that need to be grouped. Thus, we define a data structure to hold all details of the task. This data structure will be created and filled with the appropriate values by the skeleton, either in the master or workers. This data structure and its fields are as follow:

```
struct mobile_task{
    int m_task_id;
```

The id of the task.

```
    void * input_data;
```

The buffer of the input data.

```
    int input_data_length;
```

The length of the input data buffer; the number of items in the input buffer.

```
    int input_data_item_size;
```

The size of one item in the input buffer; the number of bytes allocated in the memory for one input data item. This can be simple, such as integer, or complex, such as user defined structure. i.e. sizeof(<type>).

```
    void * shared_data;
```

The buffer of the shared data.

```
    int shared_data_length;
```

The length of the shared data buffer; the number of items in the shared buffer.

```
    int shared_data_item_size;
```

The size of one item in the shared buffer; the number of bytes allocated in the memory for one shared data item.

```
    void * output_data;
```

The buffer of the output data.

```
int output_data_length;
```

The length of the output data buffer; the number of items in the output buffer.

```
int output_data_item_size;
```

The size of one item in the output buffer; the number of bytes allocated in the memory for one output data item.

```
int counter;
```

This is a state field and refers to the value of the counter of the main loop.

```
int counter_max;
```

This is a state field and refers to the maximum number of iterations in the main loop.

```
void * state_data;
```

The buffer of the state data; this is also a state field. This field can be used for passing values or saving constants.

```
int state_data_size;
```

The size of the state buffer; the total number of bytes allocated for the whole state buffer.

```
long shift;
```

This value points to the location of input data in the memory in the main input buffer; this value is calculated for each task and it is very important when gathering the sub-results of the executed tasks.

```
int moves;
```

The total number of movements of this task. Each task may encounter different number of movements during its lifetime. This field also can be synchronously used with the next four fields to store/obtain some useful information while this task is visiting a concrete worker.

```
int m_dest[MAX_MOVES];
```

An array to store the ids of the workers that hosted this task as a result of mobility.

```
double m_start_time[MAX_MOVES];
```

An array to store the arrival times of this task.

```
double m_end_time[MAX_MOVES];
```

An array to store the leaving times of this task.

```
float m_avg_power[MAX_MOVES];
```

An array to store the average values of the relative computational power throughout the execution of this task on that worker. Each value is calculated based on the CPU MHz of the host node, the number of cores, and the number of active processes.

```
float m_work_start[MAX_MOVES];
```

An array to store the work done before the task arrives at this worker.

```
int done;
```

A Boolean field to check if the task is completed or not.

```
double task_move_time;
```

The total amount of time needed to move the task; this can be calculated once when the master sends this task to a worker.

```
    fp *task_fun;
};
```

A reference to the function on the worker. This value will be set by the worker when it arrives.

Most of these fields are set by the master while the timing and moving fields will be set by the workers.

During executing tasks on remote workers, the master keeps a log of all details of the tasks. To implement this, the master has a table of task reports for profiling all activities of each task. This task report is defined as follow:

```
struct mobile_task_report{
    int task_id;
    int task_status;
    double task_start;
    double task_end;
    int task_worker;
    int mobilities;
    double m_dep_time[MAX_MOVES];
    double m_arr_time[MAX_MOVES];
    struct mobile_task * m_task;
};
```

The description of fields of a task report structure is:

- `task_id`: The id of the task.
- `task_status`: The status of this task(0: waiting for running; 1: running; 2: completed; 3: moving).
- `task_start`: When the task is allocated to a worker.
- `task_end`: When the task is completed.
- `task_worker`: The id of the worker that runs this task.
- `moves`: The number of movements of this task.
- `m_dep_time[]`: An array to store the times of movements(leaving source worker); depends on moves.
- `m_arr_time[]`: An array to store the times(arriving destination worker); depends on moves.
- `m_task`: A reference to the details of the task in the master.

Some fields are set by the master at the beginning or at the end of the execution. Others are set when a notification is received from a worker about an update on a status of this task.

Worker

A worker process manages the local executions and all activities in the node so it can be called as a local coordinator. First, a worker expects to receive tasks from the master. But, within the execution, other workers may ask the current worker to accept some tasks.

To keep monitoring all running tasks in one worker, the worker needs a table of all local tasks running on this worker. Each record in this table refers to a task running locally as well as some timing information and threads relevant to that task. This table helps the worker control all hosted tasks for estimation and mobility. So When estimation is triggered, the worker will iterate through this table to estimate the total execution time of each task based on the local/global load information. Figure 3.10 shows the table structure in one worker.

Task id	*Task Details*	*Task Times*	*Task Moving*	*Task threads*	
1	…	12:18 – XX	0 0 0 0	1	0
2	…	13:44 – 15:41	0 0 0 0	2	0
3	…	14:11 – XX	0 0 0 0	3	0
…	…	…	…	…	

Figure 3.10: Tasks table at one worker.

This table is dynamically created and a record will be added to this table once a task arrives. A record in this table is implemented in the HWFarm skeleton as follow:

```
struct worker_task{
    int task_no;
    double w_task_start;
    double w_task_end;
    pthread_t task_pth;
    pthread_t moving_pth;
    struct mobile_task * m_task;
    int move;
    int go_move;
```

```
    int go_to;
    int move_status;
    struct worker_local_load * w_l_load;
    struct estimation * estimating_move;
    struct worker_task * next;
};
```

The fields of `worker_task` structure point to:

- `task_no`: The id of the task.
- `w_task_start`: The time of execution here.
- `w_task_end`: The time of completion here.
- `task_pth`: The thread that executes this task here.
- `moving_pth`: The thread that is responsible for mobility.
- `m_task`: A reference to the details of the mobile task.
- `move, to, go_move, move_status`: These four fields are used between `task_pth` thread and `moving_pth` thread for synchronising the mobility operation.
- `w_l_load`: A pointer to the history of the local load; more details about this struct are in Chapter 5.
- `estimation_move`: A pointer to a structure used by the skeleton scheduler; more details about this struct are in Chapter 5.

After creating a record for the arrived task, the worker creates a thread to run the attached function over the input data. If the arrived task was already running in another worker, a confirmation to the source worker and a notification to the master will be sent.

When the task completes, the worker updates the fields and sends the results to the master.

3.2.4.4 Mobility

To enhance dynamicity in shared computing platforms, the HWFarm skeleton is supported with a mobility feature. Mobility in HWFarm is performed transparently by the skeleton and based on the user settings. Figure 3.11 shows an overview of the mobility operation performed by the HWFarm skeleton.

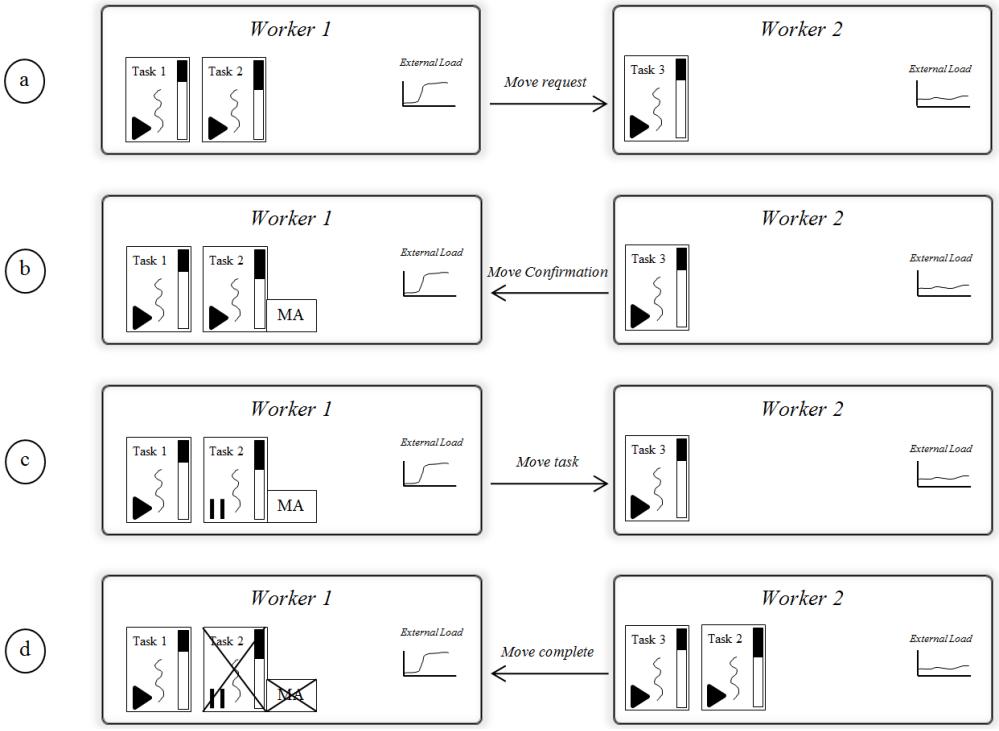


Figure 3.11: An overview of the mobility operation in the HWFarm skeleton.

To support mobility, a cooperation is required between the program and the skeleton. Hence, the program has to manage four matters: state, using references, activating mobility, and calling check-pointing.

- *State*: The HWFarm skeleton offers a structure that enables the user to define the execution state, `hwfarm_state`, outlined in Section 3.2.4.1. The user is required to specify the values for this structure before calling the skeleton.
- *Using References*: In order to control and access all the data in the task, this data should be referenced. These references are passed to the user function and therefore the user has to deal with this data using pointers as well. In this case, at any time, the worker process has access to: input data, processed data, and the state.

- *Activating Mobility*: This is accomplished when calling the skeleton. The skeleton function has an argument that specifies the status of mobility, switched on or off.

- *Check-pointing*: This operation is performed by the skeleton but under program control. To avoid blocking the task execution during intensive computation and critical memory access, it is preferred to check if there is need for mobility between two iterations. Therefore, the HWFarm skeleton offers a function which the program has to call at the end of each iteration. This function is called `checkForMobility()` and it is also a parameter in the user function. This function only checks a flag for this task and hence there is no blocking for the executing thread.

To properly move a running computation to another location, we need to move its code, its data, and the execution state to another location and then resume the computation from its stop point. The code of the computation is already available on all processes because HWFarm is based on top of MPI which has an SPMD model. Thus, the user function is defined in the memory name space of all participating processes.

The data including input, shared, output, and state is structured in the task data structures `mobile_task` and `worker_task`. These data structures will keep access to the data while the user function is running. Therefore, whenever the task stops executing, the updated data is available and ready to be transferred.

The skeleton needs a decision maker to determine when and where mobility will occur. This is performed by the skeleton scheduler guided by a performance cost model. We will explore in Chapter 4 and Chapter 5 how the skeleton scheduler takes move decisions based on the load state.

The mobility operation is a set of activities occurring in the workers involved in this operation to move selected tasks from the source worker to the destination worker. To illustrate this operation, we have worker 1 and worker 2 executing 2 tasks and one task, respectively. During the execution, the node that hosts worker 1 becomes highly loaded. In this case, when the skeleton scheduler triggers mobility

at the source worker:

(a) The skeleton sends a move request to the destination worker which checks if it is feasible to accept new tasks. See Figure 3.12.

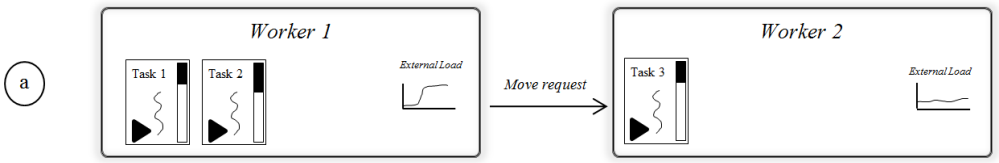


Figure 3.12: Step a of the mobility operation in the HWFarm skeleton.

(b) When a confirmation has been received from the destination worker, a thread, Mobility Agent (MA), will be created for moving a task to that destination. Then, the MA thread synchronises with the task thread until `checkForMobility()` has been called by the thread to enable check-pointing. See Figure 3.13.

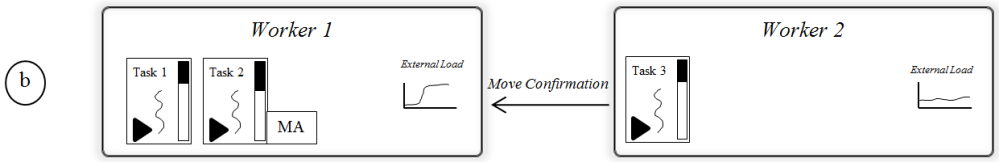


Figure 3.13: Step b of the mobility operation in the HWFarm skeleton.

(c) The MA thread sends the task data: input, output, state buffers and other task details to the destination worker. The destination worker receives the task and resumes the task execution. See Figure 3.14.

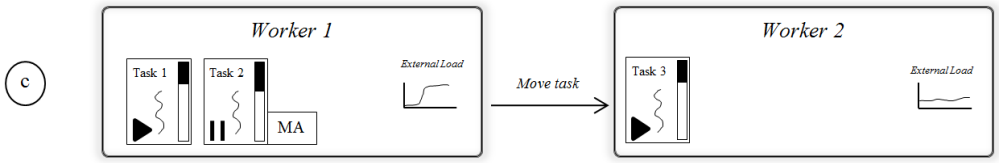


Figure 3.14: Step c of the mobility operation in the HWFarm skeleton.

(d) Before executing the received task, the worker will notify the source worker and the master. This notification informs the source worker that the task has been successfully received and its execution has been resumed. Furthermore,

the destination worker notifies the master that a task has been moved to a new location and hence the mapping of the tasks needs to be updated. However, the local task table will be updated at the destination worker. Once the source worker receives a move complete, the source worker kills the thread of the current moved task and frees the relevant resources. See Figure 3.15.

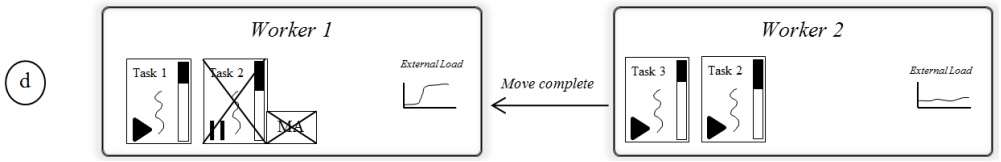


Figure 3.15: Step d of the mobility operation in the HWFarm skeleton.

Finally, the skeleton continues its activities and repeats mobility operations when needed.

3.2.4.5 Prototype

in this section, we explore the usability of the HWFarm skeleton. All code fragments presented in this section are in the C programming language, the programming language we use to develop the HWFarm skeleton. We present the prototype of the HWFarm function call as follow:

```
void hwfarm(fp user_function, int tasks,
      void *input_data, int input_data_item_size, int input_data_length,
      void*shared_data, int shared_data_item_size, int shared_data_length,
      void *output_data, int output_data_item_size, int output_data_length,
      hwfarm_state main_state, int mobility)
      {. . .}
```

This prototype shows the parameters needed to call the skeleton function. The parameters are:

- `user_function`: The function written by the user to be called by workers to manipulate the scattered data for one task.

- `tasks`: The total number of tasks.
- `input_data, input_data_item_size, input_data_length`: Input data details; outlined in Section 3.2.4.1.
- `shared_data, shared_data_item_size, shared_data_length`: Shared data details; outlined in Section 3.2.4.1.
- `output_data, output_data_item_size, output_data_length`: Output data details; outlined in Section 3.2.4.1.
- `main_state`: A data structure that holds state of the execution. This parameter is essential in optimising the execution via the HWFarm scheduler; also outlined in Section 3.2.4.1.
- `mobility`: A Boolean value to activate the mobility operations. If 0, the skeleton will work as a static skeleton.

The prototype of the user function is as follow:

```
void user_function ( hwfarm_task_data* t_data,
                     chFM checkForMobility){  }
```

This function has two parameters: `t_data` is an input parameter that holds all data. Details about this structure are outlined in Section 3.2.4.1. `checkForMobility` is a function to be called to check the mobility. Programs have to retrieve the data from the input pointer `hwfarm_task_data` and update the execution state before check-pointing. The implementation of the user function should follow the pattern:

```
void <function_name>(
              hwfarm_task_data* t_data,
              chFM checkForMobility){
    int *i = t_data->counter;
    int *i_max = t_data->counter_max;
    //retrieve the input, the output, and the state.
    while(*i < *i_max){
```

```
        //Perform the computing over the input data
        //Save the results of this iteration to the output data
        //Increment the counter
        checkForMobility();
    }
}
```

3.2.4.6 Skeleton Initialisation and Finalization

Because the HWFarm skeleton is based on MPI, the environment needs to be initialised and terminated when all executions are complete. This is done via `initHWFarm()`and `finalizeHWFarm()`.

`initHWFarm()` initializes the MPI environment to establish the communicator and create the processes. We use `MPI_THREAD_MULTIPLE` to create MPI processes with multithreaded support where we are creating many PThreads inside MPI processes.

```
void initHWFarm(int argc, char ** argv){
    int provided;
    MPI_Init_thread(&argc, &argv, MPI_THREAD_MULTIPLE, &provided);
    MPI_Comm_size(MPI_COMM_WORLD, &numprocs);
    MPI_Comm_rank(MPI_COMM_WORLD, &rank);
}
```

`finalizeHWFarm()` terminates the MPI processes:

```
void finalizeHWFarm(){
    MPI_Finalize();
}
```

3.2.5 Using the HWFarm Skeleton

Now, we will start with a simple sequential example and explain how this code can be parallelised using HWFarm.

Suppose we have the sequential C code to square numbers in a list.

```
int num_array[ARRAY_SIZE];
while( i < ARRAY_SIZE ){
    num_array[i] = num_array[i] * num_array[i];
    i++;
}
```

To use the HWFarm skeleton to parallelise this code, we have to configure the number of tasks and the chunk size. In this example, we set the number of tasks to 10 tasks where the value of `ARRAY_SIZE` is multiple of 10 and therefore all tasks have an equal chunk of data. The code for configuring the initial values is:

```
int problem_size = ARRAY_SIZE;
int tasks = 10;
int chunk = problem_size / tasks;
```

Also, we need to set the input buffer and the input parameters. Here, we initialise the input buffer with NULL because this buffer should be set at all processes. The variable `input_data_size` is set to the number of bytes to store one integer number in the host node. Finally, the variable `input_data_len` is set to the chunk size where each task will processes this number of items. The fragment of code for configuring the input is:

```
int * input_data = NULL;
int input_data_size = sizeof(int);
int input_data_len = chunk;
```

We will repeat the initialisation for the output buffer and its parameters. In this example, the number of items in the output is equal to the number of items in the input. This is not the case for all problems. The number of items in the input and in the output can be flexibly set by the user depending on the problem. This gives the HWFarm flexibility to manipulate a wide range of problems. The code for configuring the output is:

```
int * output_data = NULL;
int output_data_size = sizeof(int);
int output_data_len = chunk;
```

Then, the state of the execution needs to be set. The values of the state depend on the implementation of the problem as well as the number of items to be processed. At the beginning, each task processes a chunk of data and therefore the main counter is initialised to 0 and the maximum number of items is set to the chunk size. In this example, the state is set to NULL where in this implementation the state is not required. The code for specifying the values of the data structure `hwfarm_state` is as follows:

```
hwfarm_state main_state;
main_state.counter = 0;
main_state.max_counter = chunk;
main_state.state_data = NULL;
main_state.state_len = 0;
```

To activate mobility, the variable should have the value 1; otherwise it should have the value 0.

```
int mobility = 1;
```

Before calling the skeleton, the master should allocate the input buffer and the output buffer where the input data need to be initialised. The code is as follow:

```
if(rank == 0)
{
    //Prepare the input data
    //Prepare the output buffer
}
```

Then, the skeleton will be called with the parametrised values.

```
hwfarm( hwfarm_square, tasks,
        input_data, input_data_size, input_data_len,
        NULL, 0, 0,
        output_data, output_data_size, output_data_len,
        main_state, mobility);
```

When the skeleton function returns, the master can deal with the output data.

`hwfarm_square` is the function that will be called for each task to process a particular chunk of data. This function has the prototype outlined in the previous section. First, the user obtains the values of the counter for the main loop. The main counter values should be obtained using pointers as follow:

```
int *i = t_data->counter;
int *i_max = t_data->counter_max;
```

Then, the input and the output references will be obtained as follow:

```
int *input_p = (int*)t_data->input_data;
int *output_p = (int*)t_data->output_data;
```

Observe that all assignments in the user function should be performed through pointers to reflect the updates on the passed arrays and to keep all data, such as input, output, and counter, up to date during the execution of the task.

The main loop looks like:

```
while(*i < *i_max){
    *(output_p + (*i)) = *(input_p + (*i)) * *(input_p + (*i));
    (*i)++;
    checkForMobility();
}
```

In comparison with the sequential code, we can see that parallel code is somehow similar to serial code except using pointers and calling the check-point function, `checkForMobility()`. A call to this function is needed to complete the check-pointing and accomplish transferring the current task if necessary. Following this

approach is required to properly estimate and perform mobility during the execution of the program. Then, the dynamicity of the HWFarm skeleton is fully exploited. Figure 3.16 shows the original and modified loop when using the HWFarm skeleton.

```
while( i < ARRAY_SIZE ){
    num_array[i] = num_array[i] * num_array[i];
    i++;
}
```

(a) The original loop

```
while(*i < *i_max){
    *(output_p + (*i)) = *(input_p + (*i)) * *(input_p + (*i));
    (*i)++;
    checkForMobility();
}
```

(b) The modified loop

Figure 3.16: The main loop of the user function.

The full code of this example is as follow:

```
void hwfarm_square(hwfarm_task_data* t_data, chFM checkForMobility){
    int *i = t_data->counter;
    int *i_max = t_data->counter_max;
    int *input_p = (int*)t_data->input_data;
    int *output_p = (int*)t_data->output_data;
    while(*i < *i_max){
      *(output_p + (*i)) = (*(input_p + (*i))) * (*(input_p + (*i)));
      (*i)++;
      checkForMobility();
    }
}

int main(int argc, char** argv){
    initHWFarm(argc,argv);
    int problem_size = ARRAY_SIZE;   //number of item in the list
    int tasks = 10;                  //number of tasks
    int chunk = problem_size / tasks;// number of items in one task
    //local input data details
```

```
    int * input_data = NULL;
    int input_data_size = sizeof(int);
    int input_data_len = chunk;
    //output data details
    int * output_data = NULL;
    int output_data_size = sizeof(int);
    int output_data_len = chunk;
    //details of the main counter
    hwfarm_state main_state;
    main_state.counter = 0;
    main_state.max_counter = chunk;
    main_state.state_data = NULL;
    main_state.state_len = 0;
    int mobility = 1;
    if(rank == 0)
    {
        //Prepare the input data
        //Prepare the output buffer
    }
    hwfarm( hwfarm_square, tasks,
         input_data, input_data_size, input_data_len,
         NULL, 0, 0,
         output_data, output_data_size, output_data_len,
         main_state, mobility);
    if(rank == 0){
        //Do something with the output
    }
    finalizeHWFarm();
}
```

3.2.6 Skeleton Assessment

The design of the HWFarm skeleton has addressed a pragmatic manifesto [67] and its extension in [72]. Here, we discuss how the HWFarm skeleton met these principles:

1. *Propagate the concept with minimal conceptual disruption*: HWFarm is presented as a library or a function call in the C programming language. This avoids learning new syntax and gets benefits from C features, such as portability. Nevertheless, rewriting of the code to obtain parallel code is required. Moreover, HWFarm depends on the MPI and PThreads libraries to support communications in distributed and shared memory platforms, respectively.

2. *Integrate ad-hoc parallelism*: because the HWFarm skeleton is built on top of the most popular message passing libraries, this integrates with ad-hoc parallelism.

3. *Accommodate diversity*: The program pattern supported by the HWFarm skeleton is the loop parallelism pattern. Moreover, it is straight forward to compose multiple HWFarm function calls to solve problems in a pipeline style. However, the HWFarm skeleton is not nestable and the Divide and Conquer pattern is not supported.

4. *Show the pay-back*: To illustrate the payback, we present a skeleton that is straight forward to use and responsive to the load changes and where distribution is based on machine characteristics.

5. *Support code reuse*: In the HWFarm skeleton, the sequential code can be reused with some modifications where the structure of the code is unmodified. But there is more effort when the implementation has special behaviour, such as dynamic allocation.

6. *Handle heterogeneity*: The HWFarm skeleton supports multi-core clusters that provide heterogeneous resources without addressing GPU architectures or CPU accelerators. In addition, the HWFarm skeleton works in MPI compatible platforms with Linux based operation systems.

7. *Handle dynamicity*: The HWFarm skeleton is designed to be dynamic through raising its awareness to the external load and supporting a mobility approach to enable the skeleton to reallocate its computations amongst the nodes of non-dedicated clusters. This enhances the skeleton to handle dynamicity and adaptivity to the load state of the system.

3.3 Experiments

In this section, we present some experiments in order to show the improvement in the performance from the perspective of speed up.

3.3.1 Platform

The HWFarm skeleton is tested on a Beowulf cluster located at Heriot-Watt University. The cluster consists of 32 eight-core machines: 8 quad-core Intel(R) Xeon(R) CPU E5504, running GNU/Linux at 2.00GHz with 4096 kb L2 cache and using 12GB RAM.

3.3.2 Skeletal Experiments

In these experiments, we show the speed up when running our skeleton with different chunk sizes for the same problem. We use two applications Matrix Multiplication and Raytracer. For simplicity, we used two nodes of the Beowulf cluster to run our skeleton, one for the master and one for the worker.

The Matrix Multiplication problem is based on:

```
for(i=0;i<n;i++)                //n:row count in M1
    for(j=0;j<m;j++)            //m:col count in M2
        for(k=0;k<c;k++)        //c:col count in M1 = row count in M2
            M3[i][j]=mul(M1[i][k],M2[k][j]);
```

In the first experiment, we run a 2000*2000 Matrix Multiplication problem with different number of tasks to investigate that the skeleton achieves a speedup. The

chunk size of each run is related to the number of tasks where the problem size is fixed. The full source code can be found in Appendix A.2. Figure 3.17 illustrates a good speed-up when using several tasks to solve the same problem.

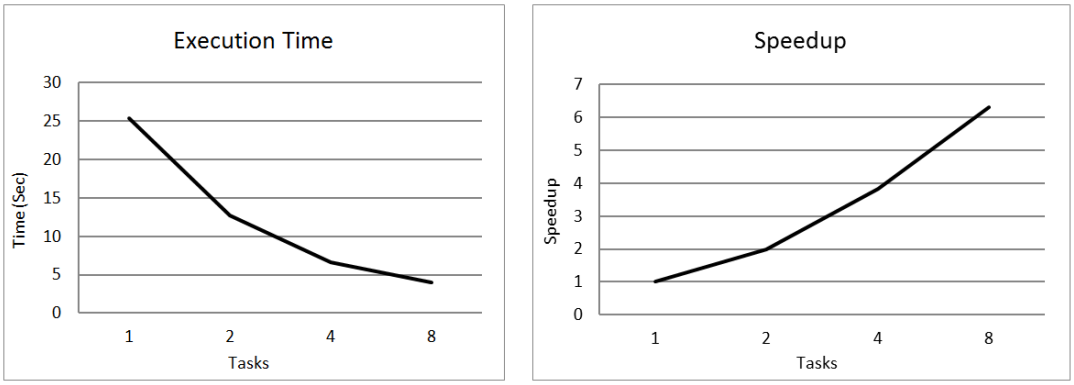


Figure 3.17: The execution time and the speedup when using the HWFarm skeleton to solve 2000*2000 Matrix Multiplication problem.

Another application of the HWFarm skeleton is Raytracer.

```
rays=generateRays(rays_count,coordinates);
scene=loadObjects();
foreach ray in rays
    imp=firstImpact(ray,scene);
    imps=addImpact(imp);
showImpacts(imps,rays_count);
```

We run the application to solve 100 rays with 20000 objects in a 2D scene. Each run has different number of tasks while the chunk size is implicitly calculated based on the number of rays and the number of tasks. The full source code can be found in Appendix A.3. Figure 3.18 shows the speedup gained when using our skeleton to solve the Raytracer problem.

Further experiments that evaluate the behaviour and the performance of the HWFarm skeleton will be discussed in Chapter 5.

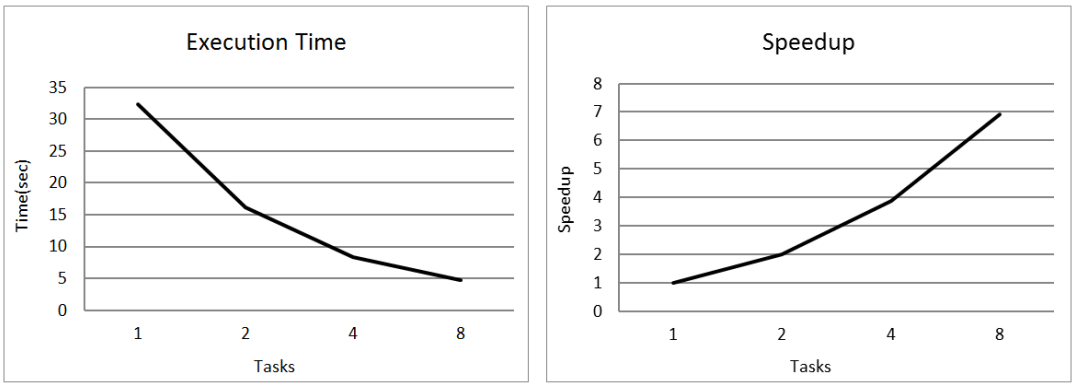


Figure 3.18: The execution time and the speedup when using the HWFarm skeleton to solve Raytracer problem with 100 rays.

3.4 Summary

In this chapter, we presented the design and the structure of the HWFarm skeleton. The HWFarm skeleton is provided as a function or a library, hosted by the C programming language, and dependent on the MPI and PThreads libraries. We followed the skeletal principles provided by Cole [67] and Danelutto et al [72] to implement this skeleton. We also showed how our skeleton fulfilled these design concepts.

The HWFarm skeleton offers an efficient tool to exploit the processing power of shared computing architectures, such as multi-core clusters. This skeleton can run as a static skeleton or mobile skeleton. The requirements of running our skeleton in static mode are as follows:

- The skeleton runs on platforms that are MPI compatible with Linux operating system.
- The skeleton can be used to execute user programs in parallel. The user program should follow the pattern outlined in Sec 3.2.4.5 where refactoring of the sequential code is needed.
- The data that will be processed by the program should also be allocated by the user. Therefore, the data buffers (input, shared and output), the unit sizes, and buffer lengths are defined based on the executing platform.
- The data in each buffer should be allocated in consecutive memory locations.

- The program has to use pointers and references in updating the output buffer.

In the mobile version, the skeleton needs more requirements to take advantage of its dynamicity. The requirements are as follows:

- The state of the program execution is defined with the state data structure, `hwfarm_state`. This structure is outlined in Sec 3.2.4.1. This structure has to be modified, especially the counter field, at the end of each iteration by the corresponding values to reflect the execution state of the program.
- At the end of each iteration, the `checkForMobility()` function should be called.
- To activate mobility, calling the skeleton with mobility switched on is required.

Either running in static or mobile mode, the skeleton runs with assumptions. In this thesis, we assume that:

- the sizes of tasks are fixed;
- the size of the task pool is static;
- the skeleton does not accept adding/removing nodes at run-time;
- and there is no dependency amongst tasks.

The experiments in this chapter show that the HWFarm skeleton gives good speed-up when running in static mode. In the next chapters, we will explore how to run the skeleton in mobile mode.

In the next chapter, we explore how HWFarm uses a performance cost model to take the decisions needed to improve the performance.

Chapter 4

Measurement-based Performance Cost Model

In the previous chapter, we presented our skeleton with a mobility approach to enable the skeleton to reschedule its computations. Here, we discuss a performance cost model used by the scheduler to produce costed decisions about the running tasks. Such a model helps the scheduler to decide the computation location on which a selected task can run faster. Therefore, this improves the performance and reduces the total execution time. We discuss the cost model used by the HWFarm skeleton in Section 4.1. Next, we show the evaluation of this cost model in Section 4.2.

4.1 Performance Cost Model

The presence of multiple applications in a shared environment may cause resource contention by the running processes. Mobility is a good solution to lighten the load and enhance the efficiency. But, mobility must be controlled and driven by concerns related to the performance goals. Hence, a cost model is needed to take accurate decisions. Accuracy of such decisions requires that the cost models should be dynamic to reflect the environment load. Nonetheless, dynamic cost models incur more overhead at run-time than static cost models.

In this thesis, we propose a dynamic performance cost model, the HWFarm cost

model. This model uses a measurement-based approach at run-time to estimate the continuation time of the running computations. This model is parametrised with dynamic parameters such as environment workload and the progress of the running computations. Our experiments show that this cost model supports the adaptivity of the HWFarm skeleton through taking accurate decisions. In this section, we explore the HWFarm cost model design and its dynamic metrics.

4.1.1 Cost Model Design

The mobility decision in the HWFarm cost model is taken when the time to complete executing a task at the current location is greater than the time to execute the same task on a remote location aggregated with the transfer cost of that task. The condition of the mobility decision is:

$$T^i > T^{mobility} + T^j; \text{ where } i! = j$$

where: T^i and T^j are the estimated times for a task at location i and at location j, respectively. $T^{mobility}$ is the predicted cost of moving a task from the source location to the destination location where transfer costs between all nodes are the same.

To develop an adequate scheduling mechanism for the HWFarm skeleton, this requires taking decisions based on the current behaviour. Therefore, we employ a performance cost model to solve this issue. Nonetheless, evolving such a model needs to take into consideration these challenges: architecture characteristics, application parameters, system load, and network delays. All these challenges need to be addressed in order to acquire the performance goals.

Architecture characteristics

To optimise the performance of HWFarm, the cost model should address the characteristics of target architectures. These architectures are usually composed of various kinds of processing units and hierarchical interconnections. To fully exploit these rapidly evolving heterogeneous resources in the shared environments, HWFarm has

to be adaptive to the platforms where it is running. This also achieves performance portability. However, due to the big influence of the architecture characteristics on performance, these characteristics need to be integrated with the cost model. Consequently, the HWFarm cost model should be architecture-independent and be able to predict the performance on the target architectures.

The architecture parameters that affect the running computations and used in architecture-independent cost models are: the speed of CPU, number of processing units, number of cores, memory, and cache. Deng [80] presented a cost model parameterised with the CPU speed. The number of processing units is also used with many cost models such as LogP [71]. L2 cache is also addressed in the cost model proposed by Khari [21].

In the HWFarm cost model, we use two static architecture parameters: the speed of the CPU and number of cores on that CPU. We assume that all cores in a node have the same clock speed. In this work, we do not address the memory and the cache.

The static information used by the HWFarm cost model can be obtained once at the start-up from the `/proc` virtual file system. These values reflect the maximum potential computational power of the current machine.

Application

Conventionally, to estimate the cost of running an implementation, cost analysis of the algorithm should be carried out. This requires knowledge of the application and the executing platform. Furthermore, this may take much effort that transcends the benefits of analysis.

In skeletal-based systems, the skeleton is adopted as a parallel subroutine to execute a parametrised user code. This generic subroutine is referred to as a black-box component [55]. Hence, there is no prior knowledge about the programs they execute. In HWFarm, the skeleton executes its tasks with awareness about their progress of execution. This is implemented with assistance from the user. This was detailed further in Chapter 3.

Parallel applications are generally computationally intensive. Such applications are typically implemented using constrained programming models. Constrained programming models or concrete coordination patterns simplify the cost modelling of these applications. Because the program model used in the HWFarm skeleton is loop parallelism, this gives the running tasks a repetitive nature.

In iteration-based applications, each iteration that manipulates the specific amount of data has an executing cost somehow similar to the cost of other iterations that process the same amount of data [235]. That is correct if the execution continues on the same platform with the same load state. But, this is not the case if the computations are irregular. We will discuss the accuracy of the estimations in irregular computations in Section 4.2.1.2. In some references, the iterations are referred to as super-steps like the BSP parallel model [123].

Therefore, in the HWFarm cost model, we used a partial execution approach to estimate the continuation times based on the past execution on the current node. This approach is also based on monitoring and measuring of the behaviour of the running computations. This approach was previously used by Yang et al [235] where they showed that this mechanism is portable and cost-effective to predict the performance. The metrics used in the model are: the elapsed time for a specific task and how much work was completed in this location. These metrics are classified as dynamic parameters that reflect the behaviour of the execution of the running tasks. The first metric can be measured dynamically while the second is obtained from the data structure of the relevant task. All details about this structure are outlined in Section 3.2.4.1. These two metrics are also used in the cost model developed by Deng [80].

System load

Selecting load metrics that characterize the system workload is crucial to the movement decisions. The information about the system load reflects the environment's state. However, we need to employ the metrics that are useful to estimate the continuation execution time from the past local load.

We identify the dynamic metrics that represent the workload of the systems:

- The load average represents the average system load over a period of time. It appears in the form of three numbers which represent the system load during the last one-, five-, and fifteen-minute period.
- The CPU utilisation refers to the percentage of usage of the CPU on all cores.
- The number of running processes refers to the number of processes and threads currently assigned to the CPU.

In HWFarm, we use the CPU utilisation and the number of running processes as dynamic input parameters of the HWFarm cost model. We exclude the load average because it depends on the number of running and runnable tasks over a past period, and its values are only updated in 3 second intervals in a typical Linux Kernel. However, these values will be obtained periodically to measure the load state of the host node. Like architecture characteristics, these values are also obtained from the `/proc` virtual file system.

Network

The performance of parallel applications may be affected by the network contention due to communication delay and latency. In order to produce accurate decisions, the network characteristics should be considered in estimating the costs.

In the HWFarm cost model, the estimated times are calculated depending on the local state on the current node and on other nodes. Because there are no inter-communications amongst the tasks, the network latency has to be considered only in mobility decisions. Therefore, to get accurate decisions for either moving a task or not, that depends also on the cost of moving a task, $T^{mobility}$. Initially, we assume that the communications are uniform within the cluster environment. Nonetheless, for more accurate decisions, we need to observe the real network properties.

Network overhead, network contention, network bandwidth, and network latency are metrics that have been used in cost modelling. An example of cost models that use network characteristics is the LogP model [71].

In HWFarm, for simplicity, we use only the network latency as an indication of whether the node is in a remote cluster or a local cluster.

As a conclusion, developing a highly accurate absolute cost model perfected for a single implementation, a specific target language, and a concrete architecture needs much effort. To overcome these challenges, the HWFarm cost model might be used for a wide range of implementations written to solve different problems with various programming languages. Consequently, we propose a dynamic, generic, architecture-independent, problem-independent and language-independent cost model. This model supports the HWFarm skeleton to enhance its adaptivity through predicting its own performance and hence the skeleton will be self-optimised.

However, the HWFarm cost model uses dynamic experimental measurements to estimate the behaviour of the computations. This dynamicity incurs an overhead that may influence the performance. We will explore further the overhead later in Chapter 5.

4.1.2 The HWFarm Cost Model

The HWFarm cost model is based on a generic cost model [80] developed by Deng, see Figure 4.1. Deng's model combines the abstract static generated model with dynamic parameters. Furthermore, this model predicts the continuation times on the current location and on other locations. This model also uses Formula 4.5 to determine mobility. Deng's cost model is used in AMPs (Autonomous Mobile Programs) and in AMSs (Autonomous Mobile Skeletons) such as automap, autofold, AutoIterator implemented in Jocaml, and Java Voyager, and JavaGo over LANs. However, Deng's model addresses the processing power of the CPU but it does not take into account the cores of that CPU. Moreover, this model takes into consideration only the local load.

We use Deng's model as a basis of our model and add more parameters that optimise the performance. This model is implemented in C and accepts any program able to run in parallel with some restrictions. Furthermore, it takes into account the heterogeneity of the resources as well as the overall system workload in the shared

$$T_{total} = T_{Comp} + T_{Comm} + T_{Coord}$$
$$T_h > T_{comm} + T_n$$
$$T_{Comm} = mT_{comm}$$
$$T_{Coord} = npT_{coord}$$
$$T_{Coord} < OT_{static}$$
$$n < \frac{OT_{static}}{pT_{coord}}$$
$$T_e = \frac{W_d}{S_h}$$
$$T_h = \frac{W_l}{S_h}$$
$$T_n = \frac{W_l}{S_n}$$

O : Overhead e.g. 5%
T_{total} : total time
T_{static} : time for static program running on the current location
T_{Comm} : total time for communication
T_{comm} : time for a single communication
T_{Coord} : total time for coordination
T_{coord} : time for coordination with a single processor(location)
T_{Comp} : time for computation
T_e : time has elapsed at current location
T_h : time will take here
T_n : time will take in the next location
W_d : the work has been done at current location
W_l : the work left
S_h : the current CPU speed
S_n : the next location CPU speed
m : number of communication
n : number of coordination
p : number of processor

Figure 4.1: Deng's cost model

environment. This awareness guides the skeleton to be more adaptive and elastic.

The HWFarm cost model, see Figure 4.2, starts with calculating the total processing power for the location where the task is running, P, Formula 4.1.

Next, the relative processing power will be calculated for the location on which the worker is allocated, R_i, see Formula 4.2.

Then, after obtaining the dynamic parameters needed for estimation: architecture characteristics, application parameters, and system load, the estimated time to complete the task at the current location can be calculated, T_i, see Formula 4.3. The previous steps will be repeated for the all participating workers in order to: calculate the total processing power, P_j, calculate the relative processing power,

R_j, and estimate the times to complete a specific task on other locations, T_j, see Formula 4.4.

$$P_i = S_i C_i \tag{4.1}$$

$$R_i = \frac{P_i}{n_i} \tag{4.2}$$

$$T_i = \frac{W_l R_e T_e}{W_d R_i} \tag{4.3}$$

$$T_j = \frac{W_l R_e T_e}{W_d R_j} \tag{4.4}$$

$$T_i > T_{mobility} + T_j \tag{4.5}$$

S_i: The CPU speed at location i
C_i: Number of cores at location i
P_i: The total processing power at location i
n_i: The number of running processes at location i
R_i: The relative processing power at location i
R_e: The relative processing power at the current location for the elapsed time
R_i: The relative processing power at the current location i
R_j: The relative processing power at the remote location j
T_i: The estimated time to finish the task at the current location i
T_e: The elapsed time at the current location i
T_j: The estimated time to finish the task at the remote location j
$T_{mobility}$: The time spent in moving the task from a location to another
W_d: Percentage of the work done
W_l: Percentage of the work left (100 - W_d)

Figure 4.2: The HWFarm cost model

Based on these estimates and the predicted cost to transfer the task between two locations, we can take a decision to keep this task running here or move it to a faster location. Thereafter, we will name Formula 4.5 as the *mobility decision formula*.

Each estimate is related to a task and depends on the work done, the work left, the elapsed time, the relative processing power during the previous task execution and the relative processing power now. The relative processing power, which is also refereed to as the load state, is the amount of processing power that a task can get when running on that node. This value is related to the characteristics of the host node and the total number of processes running on the node.

Observe that W_d is only the work done at the current location. This can easily

be measured but we need more details if the task previously has been moved in order to calculate the work left. Each task has a field that holds the amount of work processed when it leaves a location. Therefore, W_l will be the percentage of the work left for processing the remaining data based on the work done at previous locations and the work done here, at the current location. The work done is obtained from the counter fields of the `hwfarm_state` struct in the HWFarm skeleton. This struct is discussed in details in Sec 3.2.4.1.

Table 4.1 summarizes the parameters used by the HWFarm cost model.

Parameter	Description	Type	Static/Dynamic	Source
S_i	Node CPU Speed	Local/Remote	Static	Architecture
C_i	Node Core Count	Local/Remote	Static	Architecture
n_i	Number of processes	Local/Remote	Dynamic	System Load
T_e	Elapsed Time	Local	Dynamic	Application
W_d	Work done	Local	Dynamic	Application
W_l	Work Left	Local	Dynamic	Application
L_i	Network Latency	Network	Dynamic	Network

Table 4.1: Parameters of the HWFarm cost model.

Figure 4.3 shows that the HWFarm cost model is divided into two stages: local estimations and remote estimations. Local estimation, Stage 1, is parametrised with the information about the node, the application and the load state. Then, Stage 2 takes the local estimates as well as the information about the network, the application, and the other nodes in order to produce the remote estimations and finally concludes the final decision.

4.1.2.1 Mobility Cost

The mobility cost, $T_{mobility}$, is a significant component of the mobility decision formula, see Formula 4.5 in Figure 4.2. This component represents the time predicted to transfer the task to the destination node.

In HWFarm, there are three types of transfers: from the master to a worker, assigning tasks; from a worker to the master, returning results; and from a worker to a worker, task mobility. In this section, we focus on predicting the time needed to transfer a selected task to a new location.

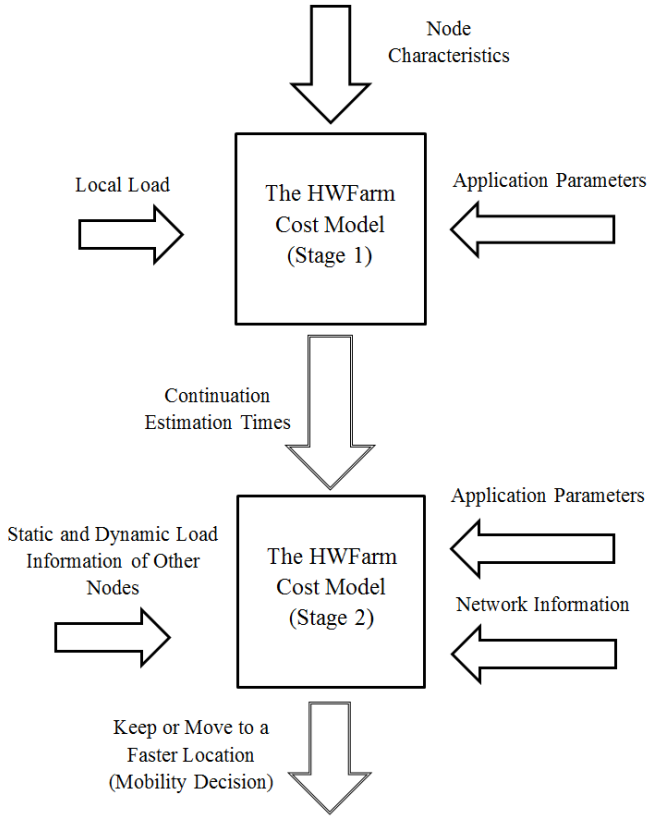


Figure 4.3: The HWFarm cost model with its parameters.

Task mobility in HWFarm is an operation that takes place when the host node is affected by an external load. This load influences all operations in this node including the network operations. Thus, the mobility cost should consider the load state of the source node. Furthermore, because mobility requires moving the execution state, this means that the size of the mobile task data may be changed according to the transfer type. Moreover, the network latency should be addressed to avoid the transfers that take a long time to complete. Such transfers add more delays to the total execution times and consequently affect the overall performance.

When transferring data through a network, there are many factors influencing the moving operation such as the data size, the network overhead, the network bandwidth, and the network latency. In HWFarm, we simplify the prediction of the transfer time through using an approach that takes into account the past transfers of the task. Also, this approach considers the changes in the transferred task in terms of data size as well as the changes of the executing environment conditions, the load state, and the network latency.

Based on the previous approach, the prediction operation in HWFarm is application-independent where it predicts the time of transferring data regardless of what the task is. Also, the prediction is architecture-independent where the network structure characteristics are featured in the times measured from the previous transfers.

Much work has been done to predict the cost of transferring data to another location. For example, Vazhkudai et al [224] proposed a framework that predicts the performance of data transfer in Grid platform based on past data transfer.

Next, we need to experiment with the impact of three factors: data size, load state, and the network latency on the transfer time. Each one of these factors will be individually investigated to find the relationship between this factor and the transfer time. Here, we use the HWFarm skeleton with a simple program, a Square Numbers application, that calculates the square of integer numbers in a one dimensional array.

Data Size

In HWFarm, the data size is the total amount of data attached to the task where this amount might be changed according to the transfer type.

In this experiment, we will investigate the impact of data size on the transfer times through measuring the times spent to transfer a task with various data sizes between two nodes/workers. Here, we measure the transfer cost of sending a task with a specific data size. Then, we compare the measured value with a new transfer cost when sending a task with a different data size. Accordingly, the changes of the transfer times are relevant to the changes of the data sizes. However, the other factors, the load state and the network latency, are constant. We repeat this experiment with various data sizes and then compare the changes of the transfer times with the changes of the data sizes. Consequently, we have a relation between the scaled transfer times and the the scaled data sizes. Figure 4.4 shows the scaled transfer times compared to the scaled data sizes. The base unit of the times is seconds while the base unit of the data size is byte.

Note that there is a dependency between the scaled data sizes and the scaled transfer times. Therefore, from this relationship, a regression analysis [58] is needed

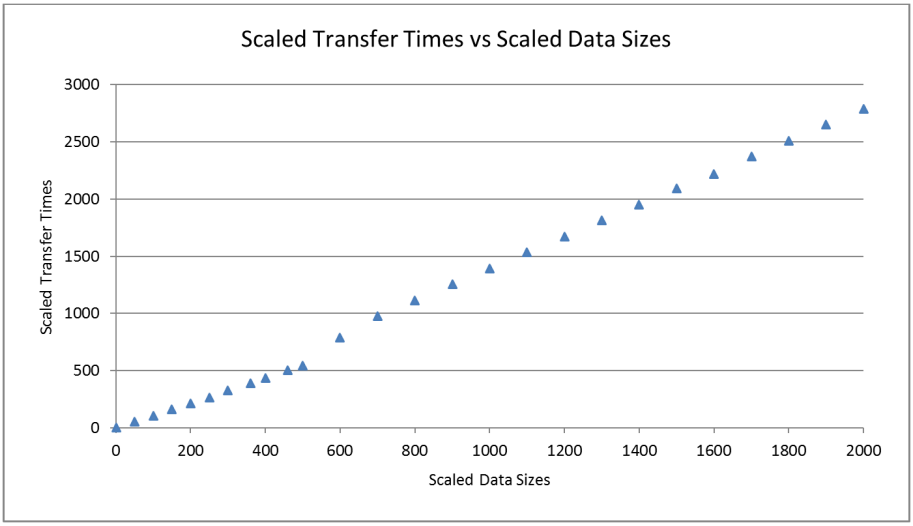


Figure 4.4: The scaled transfer times compared to the scaled data-sizes.

to predict the future transfer times based on changes of data size. We choose a power regression, $y = ax^b$, to fit the given set of data. The reason behind this selection is based on the assumption that if the data size of the task has not been changed, the prediction of the future transfer time is similar to the previous transfer cost. As a result, the power regression of the scaled transfer times compared to the scaled data sizes yields: $a = 1$ and $b = 1.023$:

$$y = x^{1.023}$$

Where: y refers the scaled transfer times while x points to the scaled data size. As a conclusion:

$$y = \frac{T_2}{T_1}, x = \frac{DS_2}{DS_1} \Longrightarrow \frac{T_2}{T_1} = (\frac{DS_2}{DS_1})^{1.023} \Longrightarrow$$

$$T_2 = (\frac{DS_2}{DS_1})^{1.023} * T_1 \tag{4.6}$$

Where:

T_1: The time of the previous transfer.

DS_1: The data size at the previous transfer.

DS_2: The data size at the next transfer

T_2: The predicted time of the next transfer.

This formula is fitted for the values of the data size at the next transfer that are less than **2000** times of the values of the data size at the previous transfer. This range of scales has been selected because the data-points afterwards are inconsistent and hence they are difficult to model.

As an example, if there is a task that has been previously transferred ($DS_1 =$ 1000 bytes and $T_1 = 1$ sec), then the predicted time to transfer the same task with changes in its data ($DS_2 = 2000$ bytes) is $T_2 = 2^{1.023} * 1 = 2.032$ sec.

Another example, there is a task ($DS_1 = 1000$ bytes) and its past transfer time is ($T_1 = 1$ sec). To predict the future transfer of this task where its data size has no change, it will be $T_2 = 1^{1.023} * 1 = 1$ sec. This means that there is no change in the predicted transfer time due to the unchanged data size.

Load State

The load state in HWFarm is referred to as the relative processing power R. Mobility between two workers occurs due to changes in R. To experiment with the effect of changes in R on the transfer times, we will measure the time spent to transfer a task in different relative processing power conditions. This example has a fixed-size task while the network latency is also fixed.

Figure 4.5 shows the scaled transfer times compared to the scaled relative processing power. The base unit of the times is second.

This Figure also shows a dependency between the scaled transfer times and the scaled relative processing powers. Therefore, to estimate the future transfer cost, we also need a regression analysis to fit these data. Here, we use a power regression for the same reason mentioned in the previous section. As a result, this regression yields: $a = 1$ and $b = -1.04$:

$$y = x^{-1.04}$$

Where: y refers the scaled transfer times while x points to the scaled relative processing powers R. As a conclusion:

$$y = \frac{T_2}{T_1}, x = \frac{R_2}{R_1} \Longrightarrow \frac{T_2}{T_1} = (\frac{R_2}{R_1})^{-1.04} \Longrightarrow$$

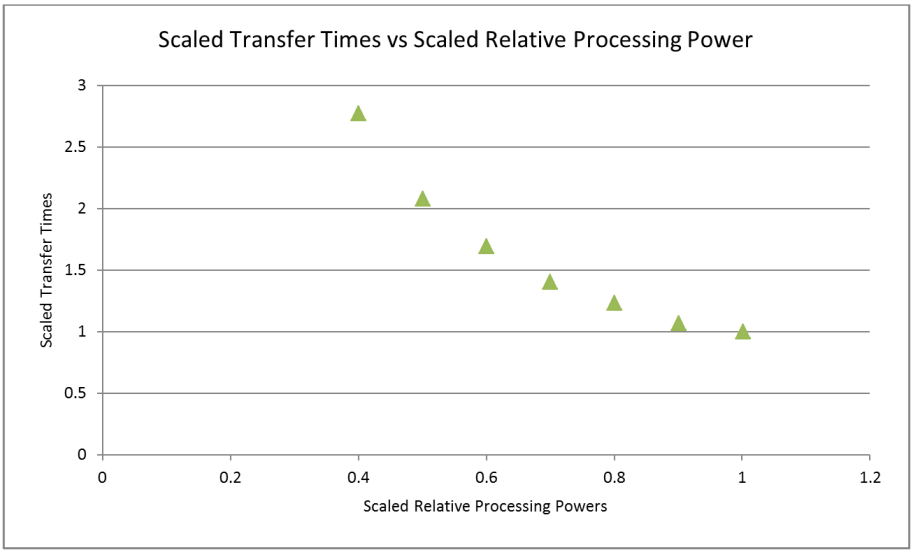


Figure 4.5: The scaled transfer times compared to the scaled relative processing power.

$$T_2 = (\frac{R_1}{R_2})^{1.04} * T_1 \tag{4.7}$$

where:

T_1: The time of the previous transfer.

R_1: The relative processing power at the previous transfer.

R_2: The relative processing power at the next transfer.

T_2: The predicted time of the next transfer.

This formula is fitted for the values of the load state that are less than **400%** where the scale of the relative processing power is ranging from 0.38 to 1. Like the effect of the data size, the data set of this range reflects a consistent behaviour of the scaled transfer time compared to the scaled relative processing power. However, the computational efficiency of the extra loaded nodes, beyond 400%, degrades badly and hence this model will produce movement decisions. Furthermore, this formula says that the next transfer time equals to the previous transfer time if there is no change on the relative processing power. This will not happen where the mobility occurs only if the current worker is highly loaded.

Network Latency

Transferring tasks amongst locations occurs through a network which may have a latency that affects the total time spent to accomplish this operation. Therefore, we need to consider the network latency in estimating the transfer time. We control the latency at a concrete location using the netem utility [118] that adds a specific amount of delay to all outgoing packets.

Figure 4.6 shows that the time of transferring a task for different network delays. These values depict that the times are equal if the latency is below a threshold value point while they increase after that value. We assume that this value is a network delay threshold where all network delays have a negligible influence on the transfer time of a task. Based on these values, the threshold is $L = 1.5ms$.

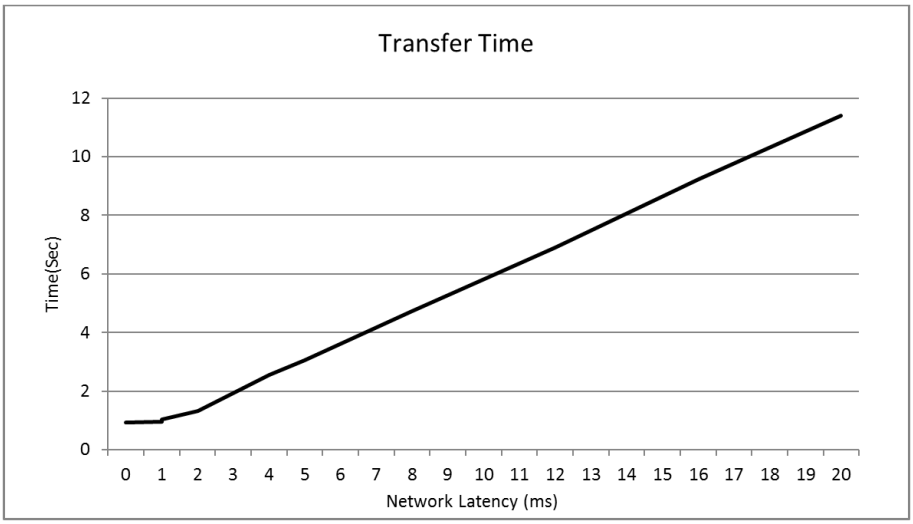


Figure 4.6: The relationship between the transfer time and the network latency.

To investigate the effect of changes of the network latency on the transfer times, we use the HWFarm skeleton with the Square program that has a fixed-size task and unchanged relative processing power. We will measure the time spent to transfer a task between two locations in different situations of network latency at the destination location.

To find the scaled network latencies, the threshold L should be taken into account. This means that any delay value that is less than 1.5ms will be assumed as L. This is true where all delays have the same effect on the transfer time.

Now, we explore the scaled transfer times compared to the scaled network latency, see Figure 4.7. The base unit of the network latency is millisecond.

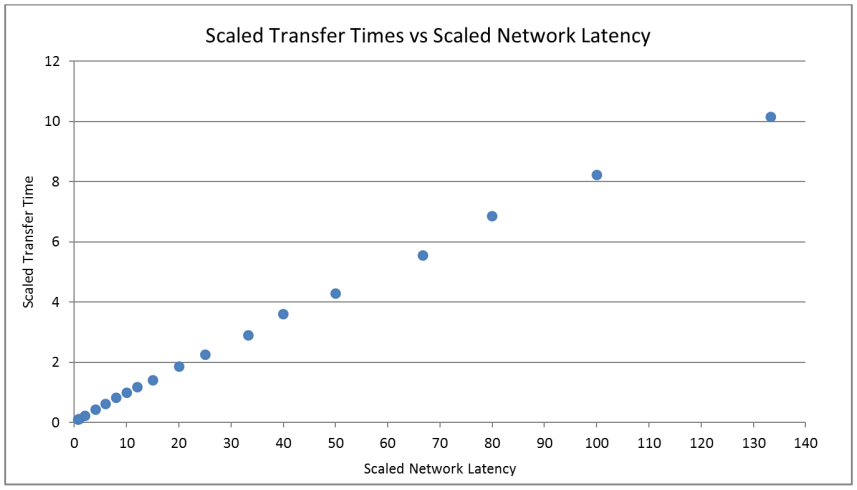


Figure 4.7: The scaled transfer times compared to the scaled network latency.

This figure also shows a dependency between the scaled transfer times and the scaled network latency. Therefore, the estimation of the next transfer time can be performed through a regression analysis to fit the data set. Also, we use a power regression that yields: $a = 1$ and $b = 0.907$:

$$y = x^{0.907}$$

Where y refers the scaled transfer times while x points to the scaled network latency. As a conclusion:

$$y = \frac{T_2}{T_1}, x = \frac{max(L_2, L)}{max(L_1, L)} \Longrightarrow \frac{T_2}{T_1} = (\frac{max(L_2, L)}{max(L_1, L)})^{0.907} \Longrightarrow$$

$$T_2 = (\frac{max(L_2, L)}{max(L_1, L)})^{0.907} * T_1 \tag{4.8}$$

Where:

T_1: The time of previous transfer.

L_1: The network latency at the previous transfer.

L_2: The network latency at the next transfer.

T_2: The predicted time of the next transfer.

L: The threshold of the network latency.

This formula is fitted for the scaled network latencies that are less than 13 times where the maximum delay applied is 20 ms. Here, the network delays that are greater than 20 ms are also difficult to model. As a result, if the network latency at the previous transfer and at the next transfer are less than ($L = 1.5$ ms), the network latency has no effect on the predicted cost. Then,

$$\frac{max(L_2, L)}{max(L_1, L)} = \frac{L}{L} = 1 \rightarrow T_2 = T_1$$

Otherwise, if either L_1 or L_2 is greater than L, Formula 4.8 is applied where the threshold L will be considered as a base to calculate the scaled latency.

Mobility Cost Summary

Now, we combine all three factors that affect the transfer times in one formula. Any changes in the data size will change the transfer time. Then, if the load state is changed, that will affect the whole operation. Moreover, if there is network latency, this will affect the transfer.

We assume that the first transfer that occurs when the master assigns a task is the baseline in predicting the mobility cost of this task. This time is referred to as $T_{assignment}$ or T_a.

The formula that predicts the transfer time of the task selected to move to a destination worker is as follow:

$$T^{mobility} = (\frac{DS_{mobility}}{DS_a})^{1.023} * (\frac{R_a}{R_{mobility}})^{1.04} * (\frac{max(L_{mobility}, L)}{max(L_a, L)})^{0.907} * T_a \qquad (4.9)$$

where:

DS_a: The data size when this task is first assigned to the current worker.

$DS_{mobility}$: The data size of this task that is supposed to be transferred to another worker.

R_a: The relative processing power when this task is first assigned to a worker.

$R_{mobility}$: The relative processing power of the current node.

L_a: The network latency when this task is first assigned to the current worker.

$L_{mobility}$: The network latency at the destination node when this task is supposed to be transferred to that node.

L: The threshold of the network latency.

T_a: The time spent when this task is first assigned to the current worker.

4.1.3 Changes to the HWFarm skeleton

To efficiently fulfil the objectives of building the HWFarm skeleton, the HWFarm performance cost model is implemented in the skeleton. This is performed through creating agents responsible for the estimating operations. These agents are called, the Estimator Agents, EAs. This supports the distributed nature of the skeleton where each worker runs an estimator agent when necessary. Details about triggering decision making will be explained in Chapter 5.

4.2 Cost Model Validation

In this section, we present experiments with the HWFarm cost model to validate the estimated execution times and the mobility decisions. We are exploring two types of computations: regular and irregular. For regular problems, we use a Matrix Multiplication application. In contrast, we experiment a Raytracer problem in a 2D scene as an example of irregular computations.

For these experiments, we test the skeleton in a Beowulf cluster located at Heriot-Watt University. This cluster consists of 32 eight-core machines (8 quad-core Intel(R) Xeon(R) CPU E5504, running GNU/Linux(2.6.32) at 2.00GHz with 4096 kb L2 cache and using 12GB RAM).

4.2.1 Execution Time Validation

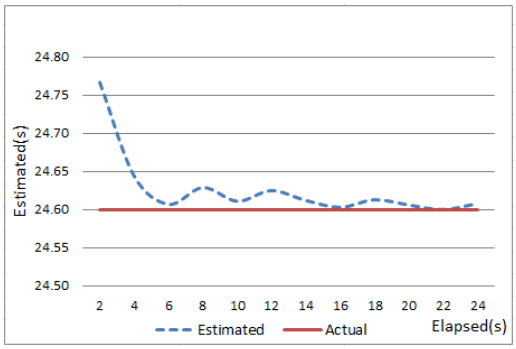
In this section, we validate the times estimated by the HWFarm cost model. These times are crucial in taking decisions to remap the running tasks over the processing units.

Size	Est-Time(Sec)	Act-Time(Sec)	Ave-Error	Per(%)	St-Dev
1000*1000	3.095	3.095	0.006	0.194	0.00042
1200*1200	5.349	5.341	0.009	0.169	0.01118
1400*1400	8.472	8.464	0.010	0.118	0.01040
1800*1800	17.972	17.936	0.036	0.201	0.03707
2000*2000	24.629	24.598	0.032	0.130	0.05363

(a) Execution time validation for different problem sizes

Time (Sec)	Est-Time (Sec)	Act-Time (Sec)	Diff	Diff %
4	24.644	24.599	0.045	**0.183**
8	24.629	24.599	0.03	**0.122**
12	24.625	24.599	0.026	**0.106**
16	24.603	24.599	0.004	**0.016**
20	24.606	24.599	0.007	**0.028**
24	24.608	24.599	0.009	**0.037**

(b) The estimated/actual time of problem 2000*2000



(c) The estimated/actual time

Figure 4.8: Execution time validation of Matrix Multiplication with one task.

4.2.1.1 Regular Computations

Regular computations have iterations where each consumes the same amount of processing time under the same load. We use Matrix Multiplication as a regular application to validate the estimations of our cost model. The pseudo-code of the Matrix Multiplication algorithm is:

```
for(i=0;i<n;i++)              //n:row count in M1
   for(j=0;j<m;j++)           //m:col count in M2
      for(k=0;k<c;k++)        //c:col count in M1 = row count in M2
         M3[i][j]=mul(M1[i][k],M2[k][j]);
```

Figures 4.8, 4.9, 4.10 and 4.11 show the estimated and actual time when running Matrix Multiplication with a range of problem sizes and various numbers of tasks.

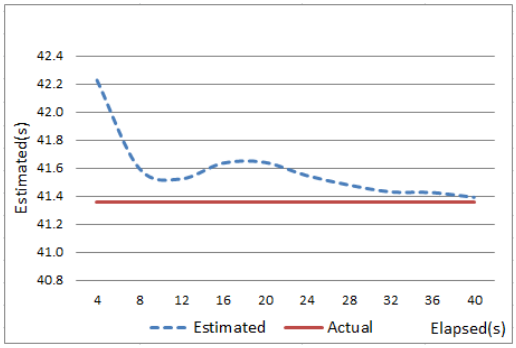
In each figure, Table (a) shows the estimated time compared to the measured actual time, with errors and standard deviation. The estimated time is the average of calculating the estimated continuation times during the execution of the problem. Table (b) shows the detailed estimated times for a task comparable to the actual time at different sample points. Figure (c) illustrates how the estimated time approaches

Size	Task	Est-Time(Sec)	Act-Time(Sec)	Ave-Error	Per(%)	St-Dev
2000*2000	1	12.249	12.196	0.053	0.435	0.07240
	2	12.242	12.192	0.050	0.410	0.07036
3000*3000	1	41.704	41.199	0.505	1.226	0.31275
	2	41.883	41.220	0.664	1.611	0.52493
4000*4000	1	97.519	97.479	0.057	0.058	0.05302
	2	97.471	97.418	0.060	0.062	0.04168

(a) Execution time validation for different problem sizes

Time (Sec)	Est-Time (Sec)	Act-Time (Sec)	Diff	Diff %
4	42.228	41.361	0.867	**2.096**
8	41.602	41.361	0.241	**0.583**
12	41.523	41.361	0.162	**0.392**
16	41.636	41.361	0.275	**0.665**
20	41.642	41.361	0.281	**0.679**
24	41.548	41.361	0.187	**0.452**
28	41.481	41.361	0.120	**0.290**
32	41.431	41.361	0.070	**0.169**
36	41.426	41.361	0.065	**0.157**
40	41.392	41.361	0.031	**0.075**

(b) The estimated/actual time of task 2 of problem 3000*3000



(c) The estimated/actual time

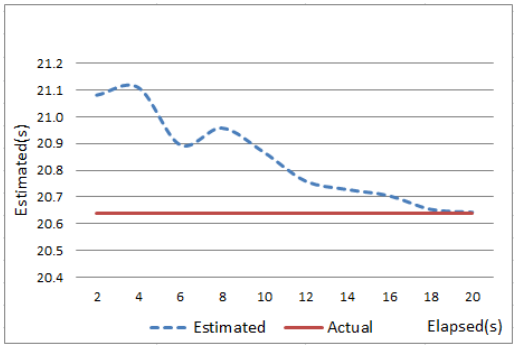
Figure 4.9: Execution time validation of Matrix Multiplication with two tasks.

Size	Task	Est-Time(Sec)	Act-Time(Sec)	Ave-Error	Per(%)	St-Dev
3000*3000	1	20.585	20.458	0.127	0.621	0.13036
	2	20.645	20.479	0.166	0.811	0.17948
	3	20.566	20.446	0.120	0.587	0.12275
	4	20.556	20.442	0.114	0.558	0.11826
4000*4000	1	50.014	49.827	0.187	0.375	0.15170
	2	50.070	49.866	0.204	0.409	0.13916
	3	49.612	49.470	0.142	0.287	0.20968
	4	49.681	49.463	0.218	0.441	0.17847

(a) Execution time validation for different problem sizes

Time (Sec)	Est-Time (Sec)	Act-Time (Sec)	Diff	Diff %
4	21.109	20.639	0.470	**2.277**
8	20.958	20.639	0.319	**1.546**
12	20.76	20.639	0.121	**0.586**
16	20.705	20.639	0.066	**0.320**
20	20.643	20.639	0.004	**0.019**

(b) The estimated/actual time of task 4 of problem 3000*3000



(c) The estimated/actual time

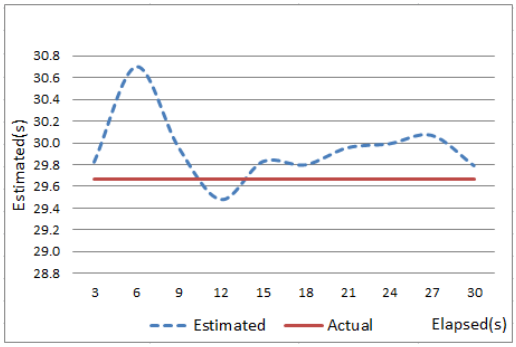
Figure 4.10: Execution time validation of Matrix Multiplication with four tasks.

Size	Task	Est-Time(Sec)	Act-Time(Sec)	Ave-Error	Per(%)	St-Dev
4000*4000	1	24.931	24.531	0.401	1.635	0.42224
	2	24.935	24.537	0.403	1.642	0.43074
	3	24.939	24.528	0.414	1.688	0.44459
	4	24.944	24.526	0.422	1.721	0.45783
	5	26.968	27.115	0.613	2.261	0.49469
	6	26.933	27.128	0.725	2.673	0.52169
	7	26.694	26.931	0.693	2.573	0.48356
	8	30.248	30.480	0.529	1.736	0.27621

(a) Execution time validation for different problem sizes

Time (Sec)	Est-Time (Sec)	Act-Time (Sec)	Diff	Diff %
6	30.703	29.667	1.036	**3.492**
12	29.48	29.667	0.187	**0.630**
18	29.799	29.667	0.132	**0.445**
24	29.993	29.667	0.326	**1.099**
30	29.792	29.667	0.125	**0.421**

(b) The estimated/actual time of task 8 of problem 4000*4000



(c) The estimated/actual time

Figure 4.11: Execution time validation of Matrix Multiplication with eight tasks.

the actual time where the solid line indicates the actual time projected backwards. These results show how the estimated time are accurate with a maximum error of 3% when comparing those times to the actual times.

Figure 4.12 summaries the results presented above. This figure depicts that the accuracy of the estimation is improved as the task progresses towards completion.

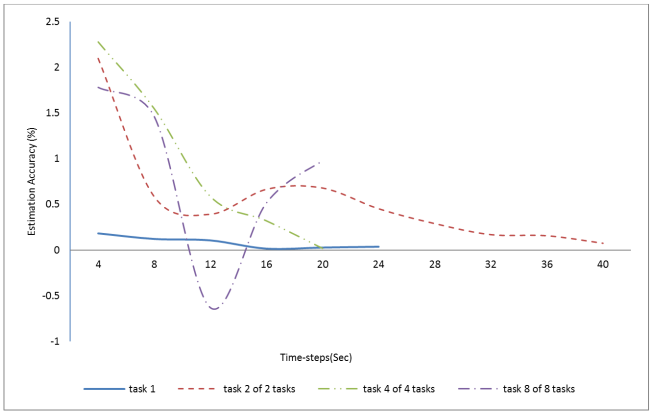


Figure 4.12: Summary of the estimation accuracy in validating the execution time in Matrix Multiplication.

4.2.1.2 Irregular Computations

In irregular computations, each iteration may need a different amount of processing time depending on the data. Here we use a simple Raytracer application where the pseudo-code of the Raytracer algorithm is:

```
rays=generateRays(rays_count,coordinates);
scene=loadObjects();
foreach ray in rays
    imp=firstImpact(ray,scene);
    imps=addImpact(imp);
showImpacts(imps,rays_count);
```

The Raytracer problem is based on rays that trace the path of light to produce an image from 2D objects in the scene. Figure 4.13 shows a 2D scene with three objects and the paths of lights, dots in the picture. Note that each ray may encounter a different number of objects which leads to different amount of computation.

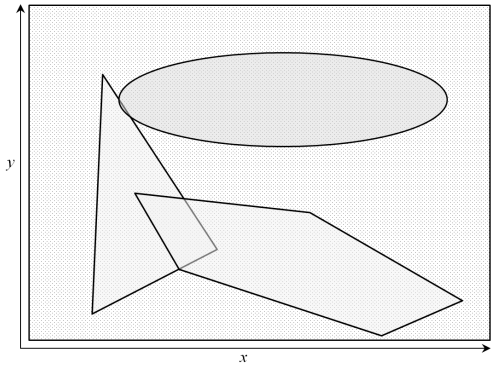


Figure 4.13: Example of 2D Raytracer problem with 3 objects in the scene.

Figures 4.14, 4.15, 4.16 and 4.17 illustrate the estimated and actual time when running Raytracer with different number of rays and various numbers of tasks.

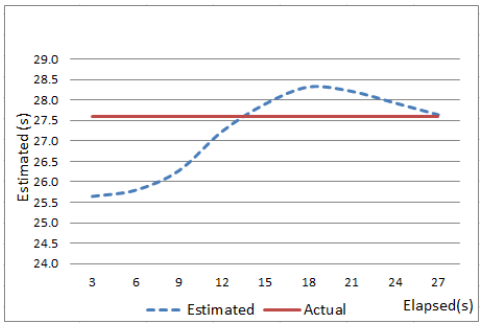
Note that in irregular computations, the estimated times are not as accurate as in regular computations. Figure 4.17 shows an error reaching 20% from the actual time. Nonetheless, the decisions made by the cost model reduce the overall execution time because the continuation cost is affected in the highly loaded workers and therefore mobility will help to execute the task faster in the lightly loaded workers.

Size(Rays)	Est-Time(Sec)	Act-Time(Sec)	Ave-Error	Per(%)	St-Dev
20	6.836	6.814	0.059	0.873	0.03079
30	15.188	15.329	0.400	2.608	0.35025
40	27.216	27.585	0.830	3.008	0.68579
50	42.844	43.431	1.285	2.959	1.01699

(a) Execution time validation for different problem sizes

Time (Sec)	Est-Time (Sec)	Act-Time (Sec)	Diff	Diff %
6	25.796	27.585	1.789	**6.485**
12	27.230	27.585	0.355	**1.287**
18	28.317	27.585	0.732	**2.654**
24	27.927	27.585	0.342	**1.240**

(b) The estimated/actual time of problem 40 rays



(c) The estimated/actual time

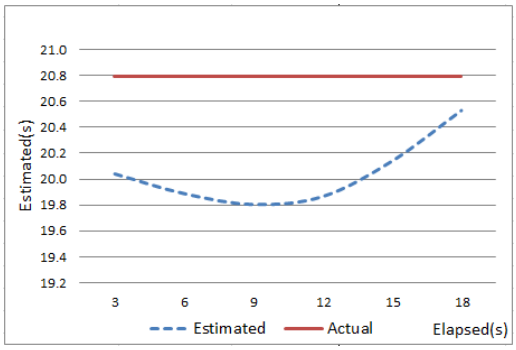
Figure 4.14: Execution time validation of Raytracer with one task.

Size(Rays)	Task	Est-Time(Sec)	Act-Time(Sec)	Ave-Error	Per(%)	St-Dev
30*30	1	7.208	7.420	0.213	2.864	0.09687
	2	7.652	7.315	0.337	4.607	0.33517
40*40	1	13.273	13.811	0.539	3.899	0.23142
	2	13.776	13.211	0.565	4.277	0.49087
50*50	1	20.044	20.794	0.750	3.605	0.26754
	2	22.984	21.702	1.282	5.907	0.80755

(a) Execution time validation for different problem sizes

Time (Sec)	Est-Time (Sec)	Act-Time (Sec)	Diff	Diff %
3	20.040	20.794	0.754	**3.626**
6	19.888	20.794	0.906	**4.357**
9	19.804	20.794	0.99	**4.761**
12	19.866	20.794	0.928	**4.463**
15	20.139	20.794	0.655	**3.150**
18	20.529	20.794	0.265	**1.274**

(b) The estimated/actual time of problem 50 rays



(c) The estimated/actual time

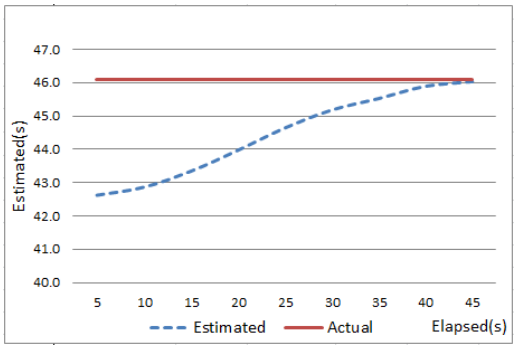
Figure 4.15: Execution time validation of Raytracer with two tasks.

Size(Rays)	Task	Est-Time(Sec)	Act-Time(Sec)	Ave-Error	Per(%)	St-Dev
50*50	1	10.307	10.365	0.058	0.560	0.04214
	2	10.777	11.150	0.373	3.345	0.32585
	3	11.940	11.563	0.377	3.258	0.14325
	4	9.965	9.891	0.074	0.752	0.06602
100*100	1	39.158	39.296	0.138	0.352	0.10103
	2	44.451	46.076	1.625	3.526	1.30430
	3	46.500	44.573	1.927	4.324	0.83220
	4	41.109	40.610	0.499	1.228	0.49682

(a) Execution time validation for different problem sizes

Time (Sec)	Est-Time (Sec)	Act-Time (Sec)	Diff	Diff %
5	42.624	46.076	3.452	**7.492**
10	42.864	46.076	3.212	**6.971**
15	43.342	46.076	2.734	**5.934**
20	43.969	46.076	2.107	**4.573**
25	44.638	46.076	1.438	**3.121**
30	45.178	46.076	0.898	**1.949**
35	45.524	46.076	0.552	**1.198**
40	45.892	46.076	0.184	**0.399**
45	46.032	46.076	0.044	**0.095**

(b) The estimated/actual time of problem 100 rays



(c) The estimated/actual time

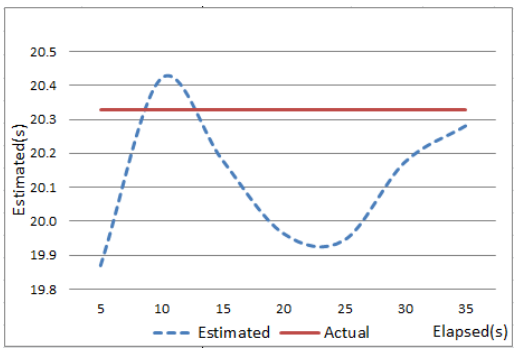
Figure 4.16: Execution time validation of Raytracer with four tasks.

Size(Rays)	Task	Est-Time(Sec)	Act-Time(Sec)	Ave-Error	Per(%)	St-Dev
100*100	1	20.418	20.717	0.328	1.585	0.34545
	2	20.119	20.328	0.235	1.157	0.16234
	3	26.109	26.172	0.789	3.015	1.04277
	4	39.525	32.863	6.662	20.271	4.64025
	5	38.298	32.471	5.827	17.945	4.07632
	6	32.070	27.700	4.370	15.777	3.29234
	7	22.355	21.277	1.078	5.069	1.24830
	8	20.339	20.204	0.203	1.003	0.25247

(a) Execution time validation for different problem sizes

Time (Sec)	Est-Time (Sec)	Act-Time (Sec)	Diff	Diff %
5	19.870	20.328	0.458	**2.253**
10	20.421	20.328	0.093	**0.457**
15	20.181	20.328	0.147	**0.723**
20	19.965	20.328	0.363	**1.786**
25	19.944	20.328	0.384	**1.889**
30	20.174	20.328	0.154	**0.758**
35	20.281	20.328	0.047	**0.231**

(b) The estimated/actual time of problem 100 rays



(c) The estimated/actual time

Figure 4.17: Execution time validation of Raytracer with eight tasks (100 rays).

Figure 4.18 summaries the results presented above. Also, this figure illustrates that the estimation gives more accuracy while the elapsed time becomes longer.

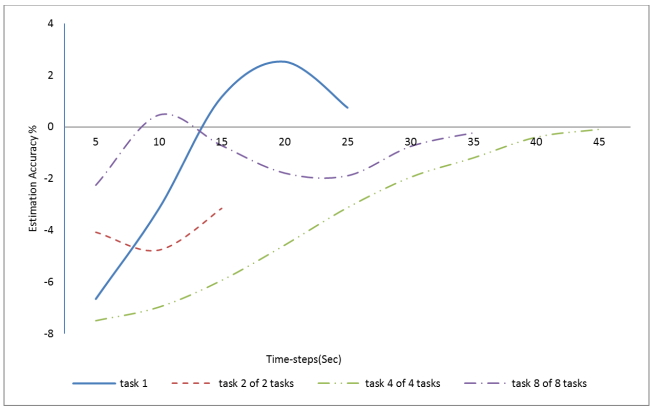


Figure 4.18: Summary of the estimation accuracy in validation the execution time in Raytracer.

4.2.2 Mobility Decision Validation

As defined in the mobility decision formula, Formula 4.5, the mobility decision should be taken when the current task may run faster at another location. We need to validate that the decision is taken as expected. To investigate the accuracy of the mobility decision, we run a Matrix Multiplication problem composed of one task using our skeleton on two locations under three different execution modes: the original mode (O) with mobility off and no load, the load mode (L) with mobility off and load, and the mobility mode (M) with mobility on and load. Figure 4.19 shows the estimated continuation times for one task calculated frequently in 3 seconds period. In this figure, each table refers to a concert mode where the first column in each table refers to the estimated times at Location 1 while the second column refers to the estimated times at Location 2. Moreover, the bold numbers refer to the estimated times of the task on that location. In mode O, the table shows that the estimated times for both locations are the same because both locations have the same relative processing power. In mode L, we apply an amount of load on the first location after 3 seconds to make it highly loaded. The results show how the task is affected by the load applied on Location 1 while the cost model gives an estimate that the task can run faster on Location 2. When activating the mobility, in mode

M, and after applying the load, the cost model finds that Location 2 is faster than the current location so that the task will be moved to Location 2 to gain better performance than staying at Location 1.

Table 4.2 summarises the execution times of the Matrix Multiplication problem in the three execution modes. In mode O, the actual execution time is 25.56 seconds. When the load is applied, in mode L, the execution time becomes 35.068 seconds and therefore the degradation is 9.508 seconds. Because of mobility, the execution time is improved by 7.127 seconds compared to the execution time at mode L. Consequently, this mobility compensates for the load condition occurred at location 1 by $7.127/9.508 * 100 = 74.96\%$.

Time	Estimated times(S)	
(Sec)	Loc1	Loc2
3	**24.614**	24.614
6	**24.602**	24.602
9	**24.598**	24.598
12	**24.570**	24.570
15	**24.575**	24.575
18	**24.577**	24.577
21	**24.565**	24.565
24	**25.568**	25.568

(a) Times in Mode O

Estimated times(S)	
Loc1	Loc2
24.720	24.720
37.357	28.722
36.052	28.590
36.052	29.409
35.955	30.157
35.319	30.512
35.254	31.283
36.373	32.147
35.147	32.842
35.595	33.628
35.064	34.418

(b) Times in Mode L

Estimated times(S)	
Loc1	Loc2
24.614	24.614
34.223	26.443
32.781	**27.964**
32.049	**27.978**
31.259	**27.947**
30.523	**27.958**
29.756	**27.944**
29.015	**27.952**
28.255	**27.943**

(c) Times in Mode M

Figure 4.19: Execution times for a Matrix Multiplication task (2000*2000) on 2 locations

	Mode	Execution Time	Difference
Mobility off & no load	O	25.56	X
Mobility off & load	L	35.068	9.508
Mobility on & load	M	27.941	-7.127

Table 4.2: Summary of the results of mobility decision validation in Matrix Multiplication.

In the irregular computation, Raytracer, we also run the skeleton in three execution modes: O, L and M on two locations. Table 4.3 shows the execution times in these modes. Observe that with mobility, the execution time is improved by 12.782

seconds while it is degraded by 14.144 seconds without mobility. As a result, the componsation here is $12.782/14.144 * 100 = 90.37\%$. Detailed results for Raytracer can be found in Figure 4.20.

In conclusion, in these experiments, we can see how the cost model informs a good decision to move the task to a new location. This costed decision and the corresponding movement operation reduce the total execution time of the task.

Time	Estimated times(S)	
(Sec)	Loc1	Loc2
3	**24.342**	24.343
6	**24.355**	24.356
9	**24.994**	24.994
12	**25.977**	25.978
15	**26.604**	26.605
18	**26.889**	26.890
21	**26.644**	26.645
24	**26.337**	26.338

(b) Times in Mode O

Estimated times(S)	
Loc1	Loc2
24.428	24.433
29.548	23.960
32.176	26.674
34.270	28.985
35.325	30.508
36.698	32.275
37.957	33.954
38.912	35.399
39.919	36.882
40.471	38.021
40.447	38.720
40.425	39.422
40.198	39.964

(c) Times in Mode L

Estimated times(S)	
Loc1	Loc2
24.401	24.405
34.924	28.049
32.723	**26.261**
33.528	**27.667**
33.339	**28.352**
32.562	**28.609**
31.145	**28.400**
29.344	**27.916**
27.703	**27.542**

(d) Times in Mode M

Figure 4.20: Execution times for a task (raytracer with 40 rays) on 2 locations

	Mode	Execution Time	Difference
Mobility off & no load	O	26.133	X
Mobility off & load	L	40.277	14.144
Mobility on & load	M	27.495	-12.782

Table 4.3: Summary of the results of mobility decision validation in Raytracer.

4.2.3 Mobility Cost Validation

The HWFarm cost model seeks to find faster locations that can serve the running tasks; nonetheless it is important to estimate the transfer cost to the destination location in order to produce better reallocation and improve the performance. However, the estimated mobility cost influences the selection of the target location especially when there are many remote locations involved in solving the problem.

Therefore, the mobility cost has a considerable influence on the movement decision taken by the cost model, see the mobility decision formula, Formula 4.5.

Here, we validate the mobility cost predicted by the HWFarm cost model, see Formula 4.9. We again use the two applications: Matrix Multiplication and Raytracer. For each benchmark, we run different sizes of tasks with different amount of load on the host node. All measurement are collected by repeating the experiment three times.

In Matrix Multiplication, we use a problem composed of one task. The implementation we use in this experiment has matrix B as shared data amongst all workers while matrix A will be divided amongst the tasks which will be allocated to the workers. When mobility occurs, additional data will be packed with the initial task data, the output, and state data. Then, the total transferred data may become two times bigger, more or less. Table 4.4 shows the estimated mobility cost compared to the actual cost. The relative error of the estimated mobility cost (actual mobility cost) is ranging from 0.08% to 9.92%. The relative error of the estimated mobility cost (total execution time) is not exceeding 0.6%.

In Raytracer, the problem is also composed of one task. Like the Matrix Multiplication implementation, the Raytracer implementation has the objects of the scene as shared while the rays are divided amongst the workers. Each task processes a list of rays to produce a list of impacts where processing one ray produces one impact. When mobility occurs, the added data is the list of impacts produced by partially processing the list of rays as well as the state data. Table 4.5 shows the estimated mobility cost compared to the actual cost. The relative error of the estimated mobility cost (actual mobility cost) ranges from 0.27% to 24.66%. The relative error of the estimated mobility cost (total execution time) is not exceeding 0.03%.

Observe that if the initial transfer cost is too small, the error in estimating the transfer cost is big, like the Raytracer results. But, the error is small when the initial transfer cost is large, the Matrix Multiplication results. In both results, the error is very small compared to the total execution time of the computation.

4.3 Summary

In this chapter, we presented the HWFarm cost model. This model is dynamic, problem-independent, language-independent, and architecture-independent. This model uses an approach that is based on real measurements of the computations and the running environment.

This model estimates the continuation time of a task based on its progress and some metrics obtained from the executing platform. We use the mobility decision formula to take decisions about where this task can run faster, see Formula 4.5.

The progress of each task can be obtained from the HWFarm skeleton where this model is embedded in the skeleton. As outlined in Chapter 3, the skeleton has access to all running tasks and therefore it can acquire information regarding the behaviour of running these tasks.

Regarding the executing platform metrics, the cost model uses static metrics and dynamic metrics. The static metrics are the clock speed and the number of cores where we assumed that the cores of each node have the same clock speed. The dynamic metrics used in the cost mode are the CPU utilisation and the number of running processes. These metrics reflect the relative processing power or the load state of a concrete node.

We initially supposed that the communications within cluster environment are uniform. Then, we proposed a model that predicts the future transfer cost of a task based on the network latency, the task size and the load state of the system.

We validated the estimates produced by the HWFarm cost model where the error in the estimated times is ranging from 3% to 20% for regular and irregular computations. We also validated the mobility decisions where we found that this model gives accurate decisions that help the HWFarm skeleton to find a faster node to run each task. These decisions improve the total execution times where the compensation reaches to 90%.

In this next chapter, we demonstrate how HWFarm uses the cost model to reschedule the tasks in order to improve performance.

Task	Actual Execution time(Sec)	Previous Transfer time(Sec)	Estimated Mobility Cost(Sec)	Actual Mobility Cost(Sec)	Absolute Error	Relative Error (Mobility Cost)	Relative Error (Total Ex-Time)	Initial Task Size (bytes)	Load Applied %
1500*1500	10.386	0.168	0.431	0.458	0.027	5.90%	0.26%	18000764	112.5
			0.502	0.467	0.036	7.67%	0.34%	18000764	150
			0.598	0.556	0.042	7.56%	0.40%	18000764	200
			0.694	0.683	0.011	1.55%	0.10%	18000764	250
			0.791	0.812	0.021	2.59%	0.20%	18000764	300
			0.896	0.859	0.037	4.31%	0.36%	18000764	350
			0.984	0.992	0.007	0.74%	0.07%	18000764	400
2000*2000	24.448	0.297	0.762	0.748	0.014	1.88%	0.06%	32000764	112.5
			0.887	0.927	0.040	4.31%	0.16%	32000764	150
			1.055	1.117	0.062	5.55%	0.25%	32000764	200
			1.224	1.204	0.020	1.65%	0.08%	32000764	250
			1.396	1.398	0.002	0.14%	0.01%	32000764	300
			1.580	1.494	0.086	5.74%	0.35%	32000764	350
			1.633	1.486	0.147	9.92%	0.60%	32000764	400
3000*3000	77.172	0.708	1.707	1.579	0.128	8.10%	0.17%	72000764	112.5
			1.988	2.130	0.142	6.68%	0.18%	72000764	150
			2.366	2.573	0.207	8.04%	0.27%	72000764	200
			2.747	2.993	0.246	8.20%	0.32%	72000764	250
			3.125	3.411	0.286	8.40%	0.37%	72000764	300
			3.509	3.732	0.223	5.96%	0.29%	72000764	350
			3.895	4.252	0.358	8.41%	0.46%	72000764	400
4000*4000	182.573	1.258	3.031	2.850	0.181	6.33%	0.10%	128000764	112.5
			3.531	3.258	0.273	8.38%	0.15%	128000764	150
			4.201	4.518	0.317	7.02%	0.17%	128000764	200
			4.872	5.386	0.513	9.53%	0.28%	128000764	250
			5.551	6.008	0.457	7.61%	0.25%	128000764	300
			6.231	6.541	0.310	4.74%	0.17%	128000764	350
			6.928	6.923	0.005	0.08%	0.00%	128000764	400
5000*5000	355.844	1.963	4.756	4.390	0.366	8.34%	0.10%	200000764	112.5
			5.515	5.463	0.052	0.95%	0.01%	200000764	150
			6.561	7.074	0.514	7.26%	0.14%	200000764	200
			7.608	8.343	0.735	8.81%	0.21%	200000764	250
			8.672	9.174	0.502	5.47%	0.14%	200000764	300
			9.735	10.424	0.688	6.60%	0.19%	200000764	350
			10.795	10.623	0.172	1.62%	0.05%	200000764	400

Table 4.4: Mobility cost validation with Matrix Multiplication.

Task (10000 Objects)	Actual Execution time(Sec)	Previous Transfer time(Sec)	Estimated Mobility Cost(Sec)	Actual Mobility Cost(Sec)	Absolute Error	Relative Error (Mobility Cost)	Relative Error (Total Ex-Time)	Initial Task Size(bytes)	Load Applied %
100*100	14.835	0.006	0.0089	0.0117	0.003	23.668%	0.019%	480764	112.5
			0.0100	0.0111	0.001	10.378%	0.008%	480764	150
			0.0136	0.0166	0.003	18.259%	0.020%	480764	200
			0.0134	0.0165	0.003	18.890%	0.021%	480764	250
			0.0155	0.0199	0.004	22.302%	0.030%	480764	300
			0.0175	0.0194	0.002	9.942%	0.013%	480764	350
			0.019	0.023	0.004	17.125%	0.026%	480764	400
200*200	57.946	0.021	0.0316	0.0379	0.006	16.631%	0.011%	1920764	112.5
			0.0363	0.0398	0.003	8.765%	0.006%	1920764	150
			0.0434	0.0469	0.003	7.392%	0.006%	1920764	200
			0.0494	0.0449	0.004	9.966%	0.008%	1920764	250
			0.0574	0.0521	0.005	10.145%	0.009%	1920764	300
			0.0665	0.0534	0.013	24.656%	0.023%	1920764	350
			0.077	0.069	0.008	12.316%	0.015%	1920764	400
300*300	130.580	0.045	0.0724	0.0726	0.000	0.272%	0.000%	4320764	112.5
			0.0841	0.0904	0.006	6.942%	0.005%	4320764	150
			0.0999	0.1102	0.010	9.361%	0.008%	4320764	200
			0.1158	0.1371	0.021	15.490%	0.016%	4320764	250
			0.1322	0.1494	0.017	11.473%	0.013%	4320764	300
			0.1444	0.1683	0.024	14.215%	0.018%	4320764	350
			0.159	0.153	0.007	4.437%	0.005%	4320764	400

Table 4.5: Mobility cost validation with Raytracer.

Chapter 5

Optimising HWFarm Scheduling

The proposed skeleton supported with a mobility approach is guided by a cost model. Effective cost modelling requires information from the system and the application. The cooperation amongst the distributed components of HWFarm is controlled by a hybrid scheduler. This scheduler is centralised in managing the global load information and decentralised in taking appropriate mobility decisions through employing a cost model. In this chapter, we demonstrate the scheduling in HWFarm and show that this scheduler has a low overhead compared to the total execution time where all its activities occur concurrently with the running computations. The rest of the chapter is organized as follows: Section 5.1 discusses the policies of the HWFarm scheduler in. Section 5.2 shows the optimisation of scheduling activities. Section 5.3 discusses the overhead introduced by HWFarm. Section 5.4 evaluates the scheduling mechanism in behaviour and performance aspects.

5.1 HWFarm Scheduler

The HWFarm scheduler is a distributed scheduler that uses global information from all nodes to perform a new schedule. Within the node scope, the HWFarm scheduler is an application-specific thread scheduler because it only manages its threads. The HWFarm scheduler is classified as a pre-emptive scheduler because it suspends running threads and reschedules them to run on different nodes.

Using an efficient scheduling algorithm is crucial to enhance the performance of

the cluster [60]. Batch scheduling is widely used in dedicated clusters to manage non-interactive jobs. An example of a batch scheduler is IBM LoadLeveller [134]. For interactive systems, a wide range of algorithms can be used such as Round Robin Scheduling and Priority Scheduling [215]. These are common in servers and PCs. For more complex scheduling techniques, co-operative scheduling can be used like gang scheduling [95]. In such scheduling, explicit global synchronisation is used to simultaneously schedule a group of processes that belong to the same job. On the other hand, communication-driven co-scheduling techniques, like SB(Spin Block)[173], can be employed to schedule a parallel job through coordinating the communicating processes.

Now, it is important to understand the scheduling technique used in the multi-core cluster environment targeted by HWFarm. Linux is a popular operating system that is widely used for multiprocessor environments. The default scheduler in Linux is CFS (Completely Fair Scheduler) [239] which is available in Linux 2.6.23 and above. This policy maintains providing a fair amount of the processor to the processes. This policy considers the priority which ranges from 0 to 40.

Consequently, a simple scheduling technique, the local native scheduler, has been chosen for the following reasons: 1) we want to keep the implementation simple and minimise the overhead. 2) We assumed that the parallel job, the program executed by the skeleton, has no internal dependencies and therefore there are no communications amongst the tasks. Therefore, complicated scheduling such as gang scheduling or co-scheduling is not needed. 3) Due to working in a shared environment, it is not desirable to change the scheduling policy of the operating system scheduler.

In summary, the HWFarm skeleton will run on a cluster as a user-space parallel application whose processes are allocated to nodes. Each worker process and all running threads have normal priority like any other process or thread running in the system. Because there is no direct coordination between the worker and the local scheduler, all processes or threads running on an individual node will be scheduled to resources based on the local scheduling policy. However, the local scheduler will take care of the assignment of resources to the running applications. When a worker

becomes overloaded, the HWFarm scheduler lightens the load of this node through remapping its tasks to other nodes.

The HWFarm scheduling goal is reducing the total execution time and hence improving the performance. It also can be referred to as cost driven scheduling because it uses a performance cost model that suggests new faster locations. Furthermore, the overall tasks in HWFarm are independent and hence there is no need to take into consideration the communication amongst the tasks. The locality of the running tasks also is not considered. Moreover, process or thread affinity is not addressed in this thesis where any thread migration or context switching is considered as a local scheduler issue.

5.1.1 HWFarm Scheduler Components

As stated in Chapter 3, the HWFarm skeleton is composed of the master process and worker processes allocated to machines/nodes. The master process works as a global coordinator that maintains the global load information to any worker while the worker process performs as a local scheduler that manages the running tasks.

The HWFarm scheduler is decomposed into three agents that cooperate with each other in order to accomplish the scheduling:

- LA, the Load Agent, is a distributed agent responsible for locally collecting the load information on workers and keeping the load information up to date in the master.
- EA, the Estimator Agent, is responsible for taking decisions to suggest new schedules based on cost model estimations.
- MA, the Mobility Agent, is responsible for performing the transfer of a task to a destination worker.

5.1.2 HWFarm Scheduler Properties

The scheduler in HWFarm should have the following desirable properties:

- *Efficient*: the scheduler is efficient through rescheduling the tasks to enhance the performance and balance the load. This happens with no interference with the local policies.

- *Dynamic*: the scheduler is responsive and sensitive to the changes of workload of the system.

- *Transparent*: the scheduler implicitly decides when and where to move the tasks. Hence, the allocating and the reallocating of tasks occur autonomously based on the skeleton behaviour and the load changes.

- *Adaptive*: the scheduler is able to exploit new architectures and new programs. Furthermore, this gives the scheduler the ability to exploit a wide range of computational architectures.

- *Predictive*: the scheduler can estimate the future performance depending on the past behaviour within the constraints and assumptions made on the code.

- *Asynchronous*: the functionalities of the scheduler have been assigned to agents that run concurrently on the workers where these agents work together towards the global objective.

Now, we will explore the policies of the HWFarm scheduler to meet the performance goal.

5.1.3 Scheduling Policies

Being a dynamic load management system, the load scheduler in HWFarm should fulfil the following policies:

Information policy: determines the mechanism of collecting and exchanging the load information amongst the processing elements. This policy will be discussed further in Section 5.1.3.1.

Transfer policy: defines the conditions to move tasks. This is driven by the workload status of workers. A sender-initiated or push policy has been chosen because it is simple to implement. In addition, a loaded worker is able to decide

if it is better to move some tasks away from it. It is important to note that this policy is *decentralised* because each worker triggers mobility and hence this supports scalability. Deciding mobility is maintained by the worker and is not centralised in the master. Further details about this policy will be explained in Section 5.1.3.2.

Selection policy: identifies what tasks should be moved. There are different possible policies that help in selecting the tasks for movement. Some policies choose the oldest tasks while others select the new ones. Yet other policies depend on the estimation time, where the task that has the longest or the shortest estimation time will be moved. We use the estimate of the local continuation time and compare it to the estimate of the continuation time at remote locations. In this case, the slower tasks that may run faster in remote locations will be selected. This means that the most affected tasks will be selected for movement. Therefore, as much as we minimize the influence of the external load, we will improve the performance of our application.

Placement policy: specifies the location/node to which a task should be moved. Depending on the cost model, the node that has plenty of resources to serve other tasks and that is able to execute the slow tasks will be identified to receive those tasks.

The selection and placement policies are combined in the mobility policy; see Section 5.1.3.3, where the mobility decision is based on how the slow task will run faster on the chosen target location.

5.1.3.1 Load Information Exchange

Seeking an optimal redistribution of the workload needs knowledge of the environment load states. When such information is available, the estimate will be most accurate. In the HWFarm skeleton, we consider the overall workload in the system because the dynamic load information is a significant factor in the estimations produced by the cost model. Consequently, we need an effective mechanism to make this information available when needed.

Load information diffusion is a mechanism that can be used to share the load

information in the system. It is also referred to as information dissemination. Such a mechanism is used by systems that need to take decisions during run-time, such as dynamic/distributed load balancing, failure detection, database replication, and aggregate computation. In dynamic load balancing, a load information diffusion mechanism can be used to guide the workload redistribution. Examples of load information policies used by dynamic load balancers are: direct neighbourhood [236], average neighbourhood [241], dimension-exchange [233], and gossip-based protocol [33]. A circulation approach has been used by Alzain [7] to update the dynamic load information amongst processing elements.

Load Information Diffusion in HWFarm

In HWFarm, the master is dedicated to managing and controlling the global load information. It collects the information from all workers and keeps this information updated in order to provide it to a worker when needed.

To collect the information, the master uses a circulation approach where a message circulates across all workers to gather their load information.

As outlined in Chapter 3, the pattern used in the HWFarm skeleton is Master/Worker. We used a circulation approach in order to avoid the bottleneck when collecting the information from all participating workers. The latest information about the load is available at a concrete location so this mechanism is centralised on the master. This is very useful for having accurate decisions because the most recent global information will be available to the decision makers once they request it. Experiments showed that this approach has a low overhead. More details about the overhead will be discussed in Section 5.3.2.

At the start-up of the skeleton, the master creates a load agent which is responsible for triggering the collecting operation. After creating the load agent, a logical table, WorkerLoad, of load information will be created. This table is dynamically maintained by the master and lists all details about the load states of the participating workers/nodes. In this logical table, each record/row represents the load information for a worker. This table is implemented in C via a linked list of `worker_load` data structure that has the definition:

```
struct worker_load{
   int worker_id;
   int m_id;
   int current_tasks;
   int total_tasks;
   int status;
   int w_cores;         //Static metric
   float w_cpu_speed;   //Static metric
   double w_cpu_uti;    //Dynamic metric
   int w_running_procs; //Dynamic metric
   struct network_times net_times;
};
```

The fields of this structure refer to:

- `worker_id`: The id of the worker.
- `m_id`: The id of the message triggered by the load agent.
- `current_tasks`: The number of tasks that are currently running at that worker.
- `total_tasks`: The total number of tasks processed at that worker.
- `status`: The status of the worker: 0: free; 1: busy; 2: requesting the latest load details; 3: involved in mobility.
- `w_cores`: A static value that refers to the number of cores.
- `w_cpu_speed`: A static value that refers to the processer speed.
- `w_cpu_uti`: A dynamic value that refers to the CPU utilisation.
- `w_running_proc`: A dynamic value that refers to the number of running processes
- `net_times`: A data structure that holds the network delay information.

The field `net_times` stores the initial and current network delay of this node. This network delay information will be used by the cost model to estimate the mobility cost. The `network_times` data structure has the definition:

```
struct network_times{
   double init_net_time;
   double cur_net_time;
};
```

Where:

- `init_net_time`: The initial network delay of this worker.
- `cur_net_time`: The current network delay of this worker.

The WorkerLoad table will be updated periodically in order to keep up to date with the load state of the system. As discussed in Chapter 4, the cost model requires the latest load information to accurately estimate the times and then makes decisions. However, our experiments show that collecting the load information runs concurrently and incurs low overhead. Accordingly, in HWFarm, we chose one second as a refresh rate of the collection to keep the load updated globally with the master. This rate has been chosen to make a trade-off between taking inaccurate decisions and increasing the overhead of the collection. As previously mentioned, taking inaccurate decisions is caused by using old load information where the refresh rate is large. In contrast, decreasing the rate will increase the overhead incurred by the load agents.

The collecting operation starts at the master where the load agent sends an empty load message to a worker. Next, the receiving worker appends its load information in the load message and circulates it to the next worker. When the load message is full of information, the final worker sends the message to the master. Then, the master updates the current load information with the latest information; see Figure 5.1.

At each worker, the load agent is responsible for obtaining the local load. Then the load will be stored in a data structure that can be used later by other agents.

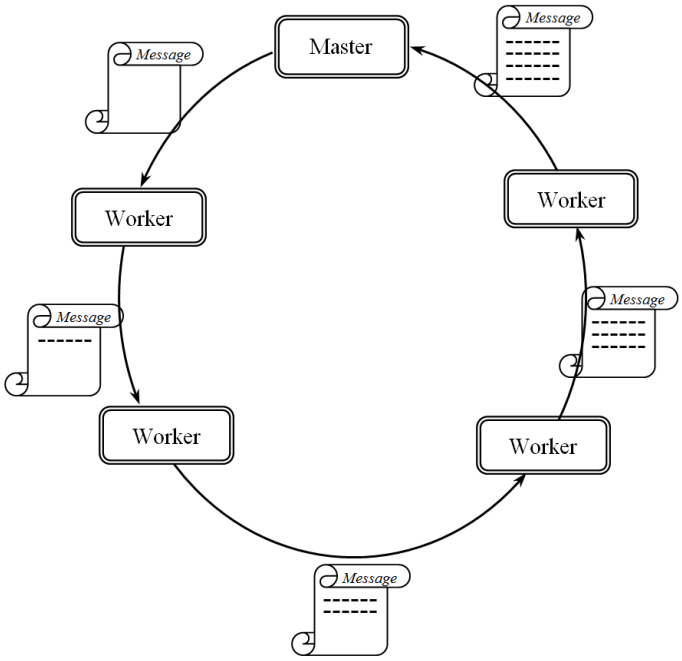


Figure 5.1: The circulating approach used to diffuse the load information in HWFarm.

This data structure is similar to the `worker_load` data structure illustrated above. This local information will be periodically updated and sent via the circulated load message to the master to be used when any worker needs this information.

5.1.3.2 Transfer Policy

Triggering the estimation operation depends on the situation in which the worker can be considered to be overloaded. In this case, the worker is not able to serve the applications or, in other words, there are no resources to meet the increase in demands. The HWFarm scheduler responds to this condition through starting an estimator agent at that worker to check the affected tasks.

Each worker has a load agent, LA, which periodically obtains dynamic metrics such as the CPU utilisation and the number of running processes. The update rate of this operation is one second. This rate has been chosen because the worker should be aware of its load to take appropriate decisions.

When reading the load information, it can easily be observed when the worker becomes loaded. But, experiments showed that it is difficult to judge that a worker is highly loaded from one reading because the processors have an unsteady nature.

This unsteadiness in the load is because the processor supports a multitasking environment where an arbitrary number of processes may use the resources for a short period of time. Hence, it is not necessary to take an action if there are processes that use the processor for a short period.

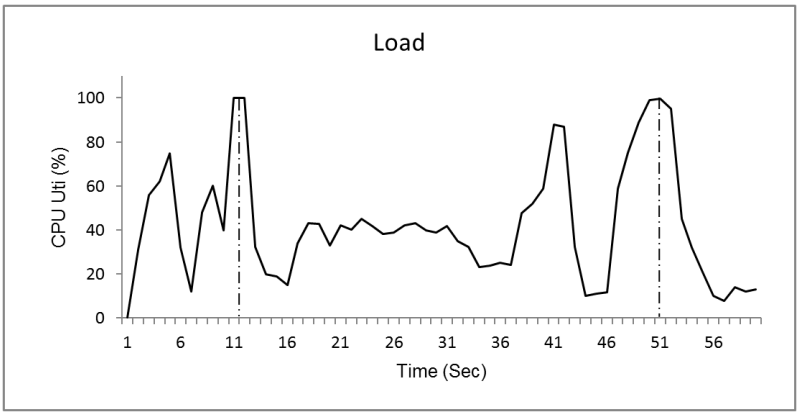


Figure 5.2: Load state of a normal loaded node.

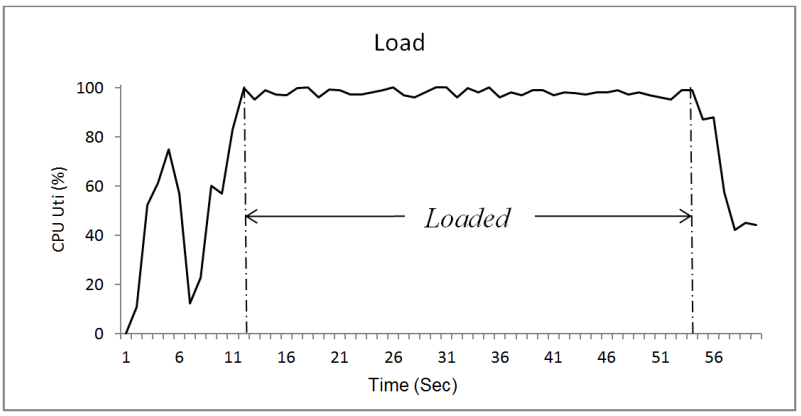


Figure 5.3: Load state of a highly loaded node.

Figure 5.2 shows an example of the CPU utilisation of a node for one minute. At second 11.5, the CPU utilisation is 100% and hence the node is loaded but afterwards the workload becomes ordinary. Then, at second 52.4, the load becomes 100% and decreases again to be normal. In this scenario, there is no need to incur the overheads in estimating and mobility where all tasks are running normally.

In contrast, Figure 5.3 shows an example of a node loaded with multiple applications where after second 12.4 many processes ask for resources and the CPU is fully utilised.

Here, we propose a policy to trigger the estimation based on multiple readings. This policy depends on checking if the following condition is true for three consecutive readings. The reason of choosing three readings is finding a balance between the overhead of the estimation operation when the worker is not actually loaded and the delay of triggering the estimation operation which affects the running tasks. This to some extent implies that the load in the worker is not occasional and thus the HWFarm tasks will be affected by this load.

$$\frac{R_h}{S_h} < \beta \tag{5.1}$$

where:

R_h: The relative processing power at the current location

S_h: The CPU speed at the current location

β : The load threshold

β is the threshold of the loading state at which it can be decided that this node is loaded. Then, a delay will occur to the running processes on the future if the load stayed steady or became worse. In this thesis, we use $\beta = 0.95$ as a threshold where we empirically found this value.

This policy will avoid the redundancy of mobility amongst the workers because it starts the estimation operation when the current worker is really loaded and takes accurate decisions if needed.

5.1.3.3 Mobility Policy

To take decisions for scheduling the local running tasks, estimation operations for the continuation and transfer times of the running computations are required. The estimation of the continuation time compared to the continuation times on other locations reflects the progress of running these computations on the current location in loaded conditions. Then based on the estimation of the transfer times, the mobility decision formula $T_i > T_{mobility} + T_j$ will be applied to make a decision.

Making more accurate decisions requires the latest load information. Hence, this load information of all nodes is prerequisite of these operation. Therefore, a

request for this information will be sent to the master. This invokes communication overhead; whereas, per contra, this improves the accuracy of the taken decisions. When this information is available, an estimator agent will be initialised to start the estimation operations through applying the cost model. Next, for each task running locally, estimated times to complete locally and remotely will be produced. Then, the estimator agent will issue a mobility report that includes the suggested movements of certain tasks to specific workers. The algorithm used by the estimator agent to produce the mobility report is as follows:

```
   EC_local = getEstimationCostHere(tasks);
   //Get the continuation cost and the network cost (the cost model)
   EC_remote = getEstimationCostOtherWorkers(tasks);
   improvement = 1;
   do{
      longest_task = getTheSlowestTask(tasks, EC_local);
      new_worker = getTheBestEstimate(EC_local, EC_remote);
      if(new_worker != current_worker){
         updateMobilityReport(longest_task, new_worker);
         updateEstimations(EC_local, EC_remote);
      }else
         improvement = 0;
}while(improvement);
```

This algorithm seeks to find a task mapping that improves the total execution time under the current load condition. In the estimation algorithm, first, the times for running all local tasks on the current node and on remote nodes will be estimated using the functions `getEstimationCostHere` and `getEstimationCostOtherWorkers`, respectively. Then, the next step will be repeated until finding an provably optimal mapping. In the loop, `getTheSlowestTask` function looks for the slowest task based on the array of local estimated times, `EC_local`. Then, `getTheBestEstimate` function returns the worker where this longest task can run faster. If the task can run faster on another worker, this task will be mapped to that worker and the es-

timated times will be updated based on the new mapping. Otherwise, there is no improvement to run this task on any node and the loop will end. The output of this algorithm is the mobility report or move report. This report contains the mapping of the selected tasks to the chosen workers. During the algorithm execution, there is no actual mobility occurring for any task but there is only changes in the tasks' mapping. Once the tasks' mapping has been changed the estimates should be updated where the estimation should take into consideration the new mapping because, when the tasks are rescheduled, this produces a change on the load state of the local and remote nodes.

To illustrate how this algorithm works, we demonstrate it with an example, see Figure 5.4. In this example, the skeleton has three workers involved in solving a problem with 12 tasks. Each worker processes 4 tasks. From the estimation point of view, each worker endeavours to reduce the execution time of its tasks. Hence, each worker has no idea about the tasks of other workers and their execution progress but it has knowledge of the load information of those workers. At some point, worker 3 becomes highly loaded, so an estimator agent will be created to handle the estimation operations. Then, a move report stating the affected tasks will be produced and accordingly the HWFarm scheduler will reschedule these tasks.

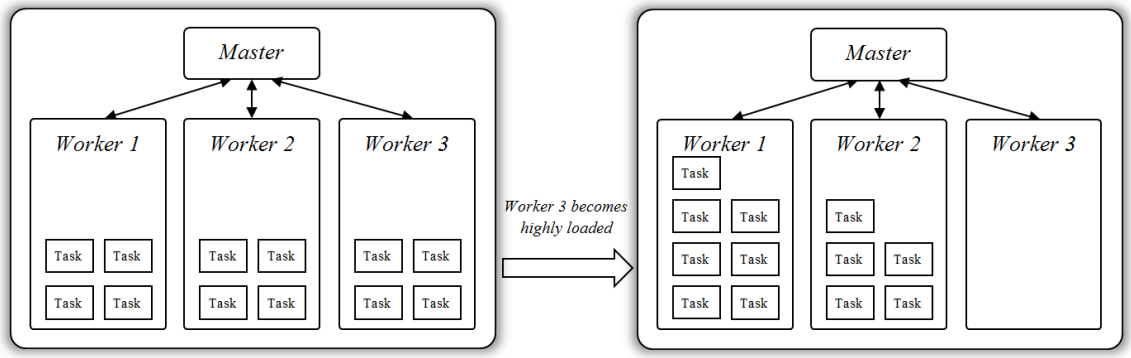


Figure 5.4: An example showing how the HWFarm scheduler reschedules the tasks when worker 3 becomes highly loaded.

Here, we are exploring the estimation operation at worker 3. Table 5.1 shows the estimated completion times of the current tasks before worker 3 gets loaded. Furthermore, the estimated move costs of all tasks to the participating workers are illustrated in Table 5.2.

Task	Local Estimated Time (Sec)
T1	48.384
T2	48.785
T3	51.917
T4	52.024

Table 5.1: The local estimated times of all tasks at worker 3.

Task	Worker	Move Cost(Sec)
T1	W1	0.449
	W2	0.449
T2	W1	0.448
	W2	0.448
T3	W1	0.449
	W2	0.449
T4	W1	0.446
	W2	0.446

Table 5.2: Estimated move costs to the remote workers.

After receiving a huge amount of load at worker 3, the estimation operation will be triggered. The estimation algorithm repeats multiple times, stages, until finding the best schedule. Each stage has new local and remote estimates, a new produced mapping, and a version of the move report, see Figures 5.5, 5.6, 5.7, 5.8 and 5.9. These stages are as follows:

Figure 5.5(a) shows the initial estimated times at stage A for all tasks. These times tell the agent that all tasks will be finished after 84.576 seconds. But, the estimates for the same tasks on other workers give better times, so the agent will select the slowest task and look for a worker that can run this task fastest, see Table 5.5(b). Thus, the first mobility suggestion is to move task 3 to worker 1. So there is a new mapping of the tasks. But this mapping, if we assume that this task has been moved to worker 1, will affect the running tasks on both worker 3 and worker 1. This means that the estimated times need to be updated based on the new mapping.

Figure 5.6(a) shows the new estimated times for the four tasks at stage B. Observe how other tasks, 1, 2, and 4, will be faster if task 3 moves to worker 1. Also, all times for the potential moved tasks will include the move cost. As an example, the estimated time of task 3 to complete on worker 1 is: $54.129 + 0.449 = 54.578$ seconds. At stage B and within the new mapping, the time to complete all four tasks is 77.742 seconds, see Table 5.6(b). Then, the estimation algorithm seeks an improved mapping and it finds that task 4 will run faster on worker 1.

(a) Estimated execution times for the local tasks.

Task	Current Mapping	Current Estimate (Sec)	Local/Remote Estimated Times (Sec)		
			W3	W1	W2
T1	W3	78.872	78.872	50.478	50.478
T2	W3	77.819	77.819	49.804	49.804
T3	W3	84.576	84.576	54.129	54.129
T4	W3	84.502	84.502	54.081	54.081

(b) The local and remote estimated times considering the current mapping.

Figure 5.5: Stage A of the estimation operation at worker 3.

(a) Estimated execution times for the local tasks.

Task	Current Mapping	Current Estimate (Sec)	Local/Remote Estimated Times (Sec)		
			W3	W1	W2
T1	W3	72.563	72.563	50.478	50.478
T2	W3	71.594	71.594	49.804	49.804
T3	W1	54.578 [a]	84.576	54.129	54.129
T4	W3	77.742	77.742	54.081	54.081

[a]The estimated time to run this task on a remote worker aggregated with the move cost to that worker.

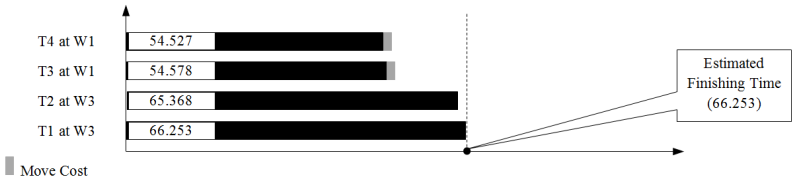
(b) The local and remote estimated times considering the current mapping.

Figure 5.6: Stage B of the estimation operation at worker 3.

Again, at stage C, the estimator finds that a task can run faster on another worker so a new mapping will be produced and the estimated times for all tasks will be updated, see Figure 5.7(a) and Table 5.7(b).

The algorithm continues to find new mapping and then it updates the estimated times for the other task, stage D, see Figure 5.8(a) and Table 5.8(b).

Now, there is one task left at worker 3 and three tasks are suggested to move to worker 1. But, task 2 still can run faster and there is an improvement if it is moved to worker 2. Hence, a new mapping will be produced and updated estimated times will result, see Figure 5.9(a) and Table 5.9(b).



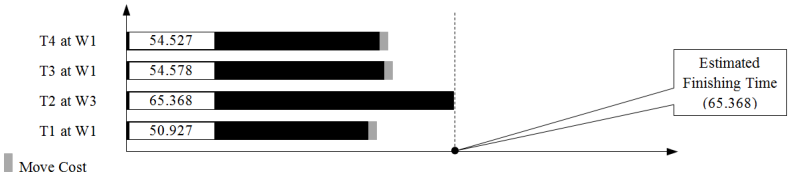
(a) Estimated execution times for the local tasks.

Task	Current Mapping	Current Estimate (Sec)	Local/Remote Estimated Times (Sec)		
			W3	W1	W2
T1	W3	66.253	66.253	50.478	50.478
T2	W3	65.368	65.368	49.804	49.804
T3	W1	54.578 [a]	77.810	54.129	54.129
T4	W1	54.527 [a]	77.742	54.081	54.081

[a] The estimated time to run this task on a remote worker aggregated with the move cost to that worker.

(b) The local and remote estimated times considering the current mapping.

Figure 5.7: Stage C of the estimation operation at worker 3.



(a) Estimated execution times for the local tasks.

Task	Current Mapping	Current Estimate (Sec)	Local/Remote Estimated Times (Sec)		
			W3	W1	W2
T1	W1	50.927 [a]	66.253	50.478	50.478
T2	W3	59.143	59.143	49.804	49.804
T3	W1	54.578 [a]	71.044	54.129	54.129
T4	W1	54.527 [a]	70.982	54.081	54.081

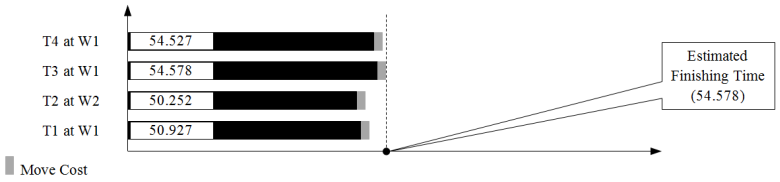
[a] The estimated time to run this task on a remote worker aggregated with the move cost to that worker.

(b) The local and remote estimated times considering the current mapping.

Figure 5.8: Stage D of the estimation operation at worker 3.

Finally, when the algorithm does not find an improved mapping, a move report will be released. In this example, this report suggests to move tasks 1, 3, and 4 to worker 1 and task 2 to worker 2, see Table 5.3. Next, a move request will be sent to the destination workers to check their availability to host these tasks.

Observe that with the new tasks' mapping, the estimated finishing time has been improved from 84.576 second to 54.578 second.



(a) Estimated execution times for the local tasks.

Task	Current Mapping	Current Estimate (Sec)	Local/Remote Estimated Times (Sec)		
			W3	W1	W2
T1	W1	50.927 [a]	59.943	50.478	50.478
T2	W2	50.252 [a]	59.143	49.804	49.804
T3	W1	54.578 [a]	64.278	54.129	54.129
T4	W1	54.527 [a]	64.222	54.081	54.081

[a] The estimated time to run this task on a remote worker aggregated with the move cost to that worker.

(b) The local and remote estimated times considering the current mapping.

Figure 5.9: Stage E of the estimation operation at worker 3.

#	Selected Tasks	Chosen Destination Worker
1	3, 4 & 1	1
2	2	2

Table 5.3: The final move report of the estimation algorithm.

5.2 HWFarm Scheduling Optimisation

The HWFarm scheduler depends on the mobility decisions to optimise the performance. In this section, we discuss some additional procedures to guarantee that the decisions taken are accurate.

5.2.1 Accurate Relative Processing Power

Decisions made using the HWFarm cost model are based on the behaviour of the computations in the past as well as the load in the last period. During running of a computation at a processing unit, it may experience different load situations that influence its progress. Hence, measuring the elapsed time without considering the slight changes in the system load may lead to inaccurate estimations of the continuation times. To enhance the estimation locally, each worker monitors and records the current system load for each running task. Therefore, each task will keep the average of local load that indicates the load encountered while it is running locally.

5.2.2 Movement Confirmation

After deciding which tasks to move to which workers, a request will be sent to those workers to check their availability. This request ensures that the load states of the destination workers have not changed during taking the decisions.

Mobility decisions may not be accurate in some situations in which the destination worker may receive an unexpected load. These new changes may invalidate the decision produced by the cost model. To address this issue, the destination worker needs to confirm task mobility. Therefore, before moving tasks to another worker, each worker should receive permission from that destination worker to start the mobility operation. This adds communication overhead which we will explore in detail in the next section. But, this policy guarantees that the decision taken are based on the updated load information.

In HWFarm, the destination worker agrees to receive tasks from any worker if it is not already busy receiving tasks from other workers. This policy avoids moving tasks at the same time from two workers to one destination workers. This is likely to happen in a dynamic load management system where multiple workers have the same load information. If the destination worker denies the move permission, no action will be taken at the source worker. This tells the source worker that there is reallocation of tasks happening in the skeleton. This reallocation will invalidate the current load information and therefore the decisions are inaccurate. This policy can be considered as a sort of negotiation between workers to avoid the location thrashing which is one of the greedy effects that has been explored by Chechina [59].

5.3 Overhead

Dynamically managing the load in an environment requires further activities that introduce overheads in the system. A balance is needed between the overhead and the endeavour towards achieving the performance goals.

The overhead activities incurred in HWFarm are categorised into three categories:

- Allocation activities: This overhead is static and incurred only at the start-up.
- Load diffusion activities: These activities are carried out in the load agents on the workers and on the master. This overhead is dynamic and runtime-activated.
- Mobility activities: These activities are carried out by the estimator and the mobility agents. This overhead is occasional and based on the load state.

Some procedures have been implemented to reduce the overhead in the HWFarm scheduler:

- Using a sender-initiated mechanism: This mechanism will reduce overhead because there is no need to estimate or perform any operation if the local load is normal.
- Improving the sender-initiated policy: We optimised the sender-initiated policy through triggering the estimation operation only if the worker is actually loaded; see Section 5.1.3.1.
- Asynchronous activities: Most of the HWFarm activities are performed concurrently to avoid blocking the running computations.

To investigate these categories of overhead in HWFarm, we ran some experiments on different architectures and with various numbers of nodes. These platforms are located at Heriot-Watt University. Table 5.4 shows the characteristics of the nodes used in these experiments.

In evaluating our measurements, we use the applications: Matrix multiplication, Raytracer, and Square Numbers.

5.3.1 Allocation Overhead

This overhead is introduced at the start-up of the skeleton in order to collect the information needed to allocate the tasks to workers based on the node's characteristics. This overhead is only at the master.

Machine Name	Number of Machines	CPU Clock Speed (MHz)	CPU Model Name	Cores	Class Code
Beowulf	32	1596.00	Intel(R)Xeon(R) CPU E5504@2.00GHz	8	A
linuxXX	86	1200.00	Intel(R) Core(TM) i7 CPU 860 @2.80GHz	8	B
osiris	1	1600.00	Intel(R) Xeon(R) CPU X5650@2.67GHz	24	C
sif, thor, and baldur	3	1400.00	AMD Opteron(tm)Processor 6380	64	D

Table 5.4: The characteristics of the architectures used in the overhead investigation.

The single activity in this overhead is applying the model outlined in Section 3.2.4.2 to calculate the portion of tasks assigned to each worker. Hence, this activity needs communication between the master and the workers to obtain the nodes' characteristics.

To explore this activity, we need to measure how much time the allocation operations take before assigning tasks to workers. In these experiments, we use different number of nodes with various architectures to study the effect of the platform on the allocation overhead.

Table 5.5 shows the times spent at the master to decide the allocation portion. These results suggest that this overhead is related to the target nodes and more specifically the number of cores of the participated nodes. Furthermore, this overhead is affected by the network delay between the master and the worker. In conclusion, the allocation operation yields negligible overhead at runtime where this overhead is target-dependant and problem-independent.

5.3.2 Load Diffusion Overhead

The load diffusion system in HWFarm is distributed amongst the components of the skeleton (the master and the workers). The activities of this system may incur overhead on these components. Here, we investigate the effect of these activities on the running tasks. The activities of this overhead are distributed amongst the load agent at the worker, the load agent at the master, and the worker process.

Nodes	Nodes Types	Time for Matrix Multiplication (Sec)	Time for Raytracer (Sec)	Time for Square Numbers(Sec)
1	1A	0.009	0.009	0.009
2	2A	0.016	0.015	0.015
4	4A	0.029	0.028	0.028
8	8A	0.056	0.055	0.055
16	16A	0.111	0.107	0.111
24	24A	0.165	0.161	0.164
32	32A	0.220	0.216	0.219
50	32A+18B	0.346	0.341	0.349
100	32A+68B	0.698	0.694	0.702
5	4A+1C	0.036	0.036	0.035
6	4A+1C+1D	0.042	0.041	0.042
8	4A+1C+3D	0.057	0.056	0.056

Table 5.5: The measured times of the allocation overhead.

5.3.2.1 Overhead at the Load Agent

The activities performed by the local load agent at workers are:

Collecting the local load: This activity periodically collects the current load states. Table 5.6 shows the measured overhead for obtaining the load details on different architectures.

	A	B	C	D
$T_{LDO\_Collecting}$ (Sec)	0.003972	0.00118	0.002315	0.010761

Table 5.6: The measured overhead for collecting the load information.

Recording R for all running tasks: Based on the optimisation procedure in Section 5.2.1, this activity calculates R from the collected load details and then records it to every local task. To investigate the time spent to perform this activity, we run some experiments on the previous architectures. The measurements show that the time does not exceed 1 nano second for each task. As a result, the total time of collecting and recording the load on a worker is:

$$T_{LDO\_LLA} = T_{LDO\_Collecting} + N * T_{LDO\_RecordingR} \tag{5.2}$$

where:

T_{LDO_LLA}: The load diffusion overhead at the local load agent

$T_{LDO\_Collecting}$: The time spent to obtain the local load information

$T_{LDO\_RecordingR}$: The time spent to record the current load state in one task

N: The total number of tasks on the current worker

As an example, if we run the skeleton on a local Beowulf cluster (architecture A), then the overhead to collect the local load information on a worker that runs 8 tasks is:

$$T_{LDO\_LLA} = 0.003972 + 8 * (0.000001) = 0.00398sec$$

Another example, if we run the skeleton on an architecture where a node has 64 cores (architecture D), then the overhead to collect the local load information on that worker that runs 64 tasks is:

$$T_{LDO\_LLA} = 0.010761 + 64 * (0.000001) = 0.010825sec$$

Observe that when running the skeleton on a worker with 8 cores, the overhead is 0.004 second while it is 0.01 second on a 64-core machine.

5.3.2.2 Overhead at the Workers

Now, we need to investigate the overhead at the worker process. This overhead is incurred when a worker receives the load message and then the worker has to append its own load information. This overhead is based on communications amongst the participating workers so the network delay has major influence on these measurements.

Table 5.7 shows the time measured at a worker process that runs on different platforms. This time includes the time to receive the load message, time to append the local load, and the time to send the new load message to a new worker.

	A	B	C	D
T_{LDO_W} (Sec)	0.000383	0.000444	0.000395	0.000352

Table 5.7: The measured overhead at one worker process.

5.3.2.3 Overhead at the Master

The master is dedicated to maintaining the global load information so the operations at the master cannot be considered as an overhead.

Table 5.8 shows the times taken to circulate the load message and the time spent to update the main worker load table, WorkerLoad. These operations are also influenced by the network delay between the master and the workers.

	A	B	C	D
$T_{LDO\_Circulating}$ (Sec)	0.000375	0.000429	0.000348	0.000356
$T_{LDO\_Updating}$ (Sec)	0.000151	0.000160	0.000143	0.000090

Table 5.8: The measured overhead at the master.

5.3.3 Mobility Overhead

The mobility overhead is expected to be the main source of overhead. In HWFrm, this overhead is concurrently introduced by the estimator agent that follows the algorithm outlined in Section 5.1.3.3. Hence, it is related to the estimation process and all mobility coordination before accomplishing the movement between the workers. This overhead is difficult to calculate at the right time where the source worker is loaded with different amount of load that causes various delays.

This overhead starts when the latest global load information is available at the source worker and ends when the mobility report is sent to the destination worker. The breakdown of this overhead is: initialising the arrays, finding the estimation costs for each task, finding the best mapping, and sending the mobility report.

Based on the mobility algorithm, the time required to produce the new mapping report in a skeleton with w workers executing N tasks is:

$$T_{MO} = T_{MO\_init} + \sum_{i=1}^{t} T^{i}_{MO\_findingEC} * N * w + \sum_{i=1}^{t} T^{i}_{MO\_findingMapping} + T_{MO\_Report} \quad (5.3)$$

where:

T_{MO}: The mobility overhead.

T_{MO_init}: The time spent to initialize the data structures.

$T^{i}_{MO\_findingEC}$: The time spent to find the estimation cost for one task. An array of estimates with N columns and w rows will be calculated to provide all possible reallocations for this task.

$T^{i}_{MO\_findingMapping}$: The time spent to find the best location for one task.

T_{MO_Report}: The time spent to send the mobility report to the new target workers. Note that this value is also affected by the network delay. Furthermore, this value depends on the number of tasks running locally and the number of involved workers. In the worst case, the overhead of sending a mobility report is:

$$T_{MO\_Report} = Min(w, t) * T_{MO\_Report\_Message} \tag{5.4}$$

One report message includes a move request for one or more tasks. If the number of tasks is greater than the number of workers, the worst case is sending a report message to every worker, w. In contrast, if the number of workers is greater than the number of tasks, the worst case is sending N report messages.

To find the time needed to process sub-operations of the mobility overhead, we run the skeleton with the previous architectures to obtain the measurements; see Table 5.9. Note that the time measured, $T_{MO\_Report\_Message}$, refers to the time needed to send one message between two workers, which is also affected by the communication overhead.

	A	B	C	D
T_{MO_init}(ms)	0.020	0.019	0.024	0.063
$T_{MO\_findingEC}$(ms)	0.001	0.001	0.001	0.002
$T_{MO\_findingMapping}$(ms)	0.001	0.001	0.001	0.001
$T_{MO\_Report\_Message}$(ms)	0.300	0.235	0.335	0.382

Table 5.9: Measurements of the sub-operations of the mobility overhead.

As an example, if the skeleton runs an application with 50 tasks over 10 workers on a Beowulf cluster, then the time needed to complete the estimation is (where each worker has 5 tasks to execute):

$$T_{MO} = 0.02 + 5 * (0.002 * 10 * 5) + 5 * (0.001) + T_{MO\_Report}$$

In the worst case, with an assumption that the average transfer time is ≈ 0.3ms, the mobility report advises to move the five tasks to five different workers so we need five messages to the target workers. So, the total time to send the report is:

$$T_{MO\_Report} = Min(t, w) * T_{MO\_Report\_Message} = 5 * 0.3 \approx 1.5ms$$

Therefore,

$$T_{MO} = 0.02 + 5 * (0.002 * 10 * 5) + 5 * (0.001) + 1.3 = 1.825ms$$

This value might be changed due to the communication delay between the workers and the characteristics of the host nodes.

5.3.4 Overhead Summary

Now we investigate the measured execution time with all categories of overhead at run-time. We run the skeleton with different number of nodes in a Beowulf cluster. We use two applications: Matrix Multiplication and Raytracer; see Tables 5.10 and 5.11. Each experiment is repeated four times with various numbers of tasks. The Raytracer application is investigated in a 2D scene with 120000 objects.

The allocation overhead is measured at the master. The load overhead is only measured at the local load agent at worker 1 when obtaining the load details. The load agent runs along with the other tasks on a worker so the numbers in the tables are the total overhead from the load agent during the worker lifetime. Moreover, the mobility overhead includes the measured times of the mobility operations and the worst case of sending the move report.

The allocation overheard is mandatory where the allocation operation is architecture-aware and the skeleton needs this information before allocating the tasks. When using 100 nodes, the allocation overhead is only 0.698 seconds; see Table 5.5.

The load diffusion overhead is important to provide the latest load information to the master and the participating workers. However, this overhead is asynchronous, dynamic, distributed, and architecture-aware. This amount can be customised by reducing the frequency of obtaining the local load but this leads to old load details

Size	Ts [a]	Ws [b]	Ts/W [c]	Ex-time(Sec) [d]	Overhead(Sec)		
					Allocation	Load	Mobility
2500*2500	5	1	5	10.693	0.008979	0.039670	0.000093+0.0003
4000*4000	10	4	2-3	26.616	0.028081	0.104663	0.000130+0.0009
6000*6000	15	6	2-3	65.619	0.043746	0.265538	0.000133+0.0009
6000*6000	30	6	5	44.703	0.043490	0.181664	0.000153+0.0015
7000*7000	28	10	2-3	81.828	0.080072	0.333914	0.000122+0.0009
8000*8000	8	2	4	210.837	0.016773	0.857721	0.000152+0.0006

[a]The total number of tasks.
[b]The total number of workers/nodes.
[c]The number of tasks on a worker.
[d]The total execution time.

Table 5.10: The measured times to execute the Matrix Multiplication application and its overhead.

Size(Rays)	Ts [a]	Ws [b]	Ts/W [c]	Ex-time(Sec) [d]	Overhead(Sec)		
					Allocation	Load	Mobility
20	1	1	1	8.115	0.008082	0.031354	0.000082+0.0003
50	4	2	2	13.264	0.014050	0.049044	0.000119+0.0006
100	10	4	2-3	22.578	0.026173	0.088936	0.000123+0.0012
150	12	3	4	42.925	0.020927	0.169810	0.000147+0.0009
200	8	5	1-2	112.922	0.034389	0.449357	0.000128+0.0015
250	20	7	2-3	70.076	0.051412	0.277574	0.000142+0.0021
300	50	10	5	40.723	0.073884	0.160297	0.000142+0.0030

[a]The total number of tasks.
[b]The total number of workers.
[c]The number of tasks on a worker.
[d]The total execution time.

Table 5.11: The measured times to execute the Raytracer application and its overhead.

available at the master. However, with one second frequency, when running our skeleton with an application for 210 seconds, the total time spent to obtain the load during that period is less than 0.86 seconds. Therefore, the load diffusion overhead is $<= 0.4\%$.

The mobility overhead is asynchronous and occurs occasionally where it is needed to accurately decide where to move the computations. The experiments showed that this overhead is very small in normal situations and it will easily be served even if the node is highly loaded. Here, this overhead is not exceeding 0.0002 second. The mobility overhead is also affected by the network delay. In this experiment, we assume that the move report overhead is at its worst case because it is difficult to

expect the move report in a load condition, as outlined in Sec 5.3.3. As an example, when we have 50 tasks and 10 workers, the overhead of sending the move report is 0.003 sec.

Consequently, these experiments show that the overhead incurred from the activities of HWFarm during the runtime is low when compared to the total execution time, less than 0.58%. In the Matrix Multiplication application, the overall overhead is ranging from 0.41% to 0.51%. Whilst in the Raytracer application the overhead ranges from 0.43% to 0.58%.

5.4 Scheduling Evaluation

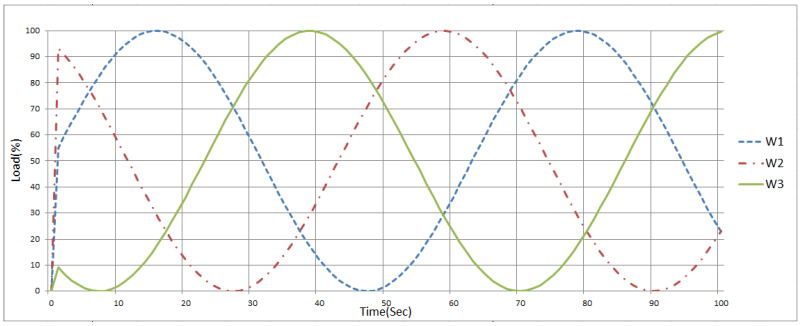
In this section, we demonstrate experiments to evaluate the HWFarm scheduling in terms of the mobility behaviour and the optimised performance of the produced schedule. We are exploring two types of computations: regular and irregular. For regular problems, we use a simple Matrix Multiplication application. In contrast, we are testing a simple Raytracer as an example of irregular computations.

The skeleton with its scheduler was tested in a Beowulf cluster located at Heriot-Watt University. The cluster consists of 32 eight-core machines (8 quad-core Intel(R) Xeon(R) CPU E5504, running GNU/Linux(2.6.32) at 2.00GHz with 4096 kb L2 cache and using 12GB RAM).

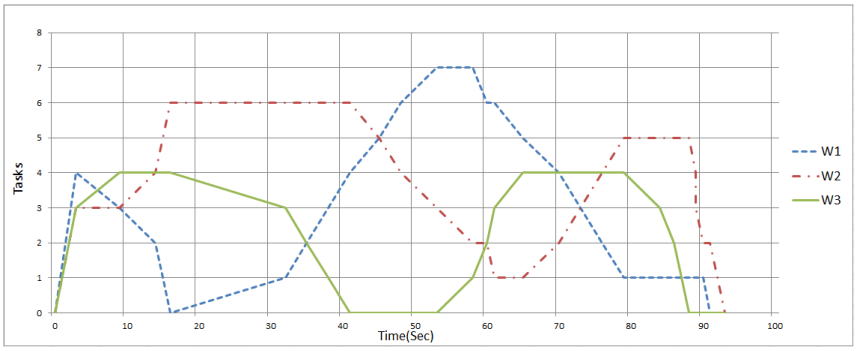
5.4.1 Mobility Behaviour Validation

To investigate that the mobility behaves as we expect, we run a Matrix Multiplication problem with 8 tasks running on 3 locations.

Figure 5.10(a) shows the changes on the load over these locations. We use our load function that generates artificial load patterns on multi-core platforms. Further details about this function will be discussed on Chapter 6. Figure 5.10(b) illustrates the behaviour of the tasks during their executions. This behaviour is influenced by the current load of the nodes. It can be seen that the HWFarm scheduler lightens the loaded nodes whenever the worker becomes loaded. This figure shows that the behaviour of the tasks is the inverse behaviour of the load.



(a) The load pattern applied to the skeleton

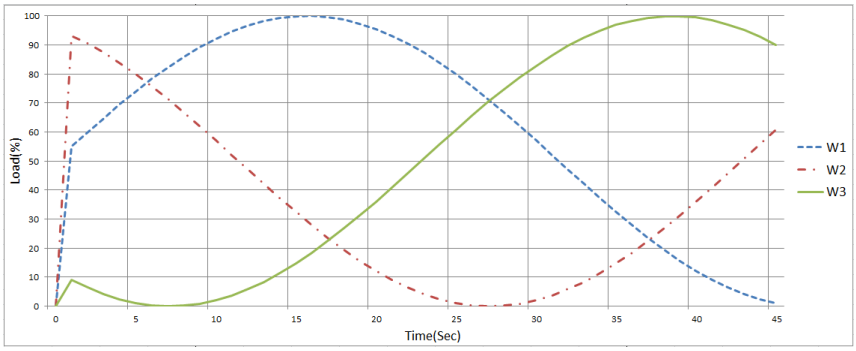


(b) The mobility behaviour

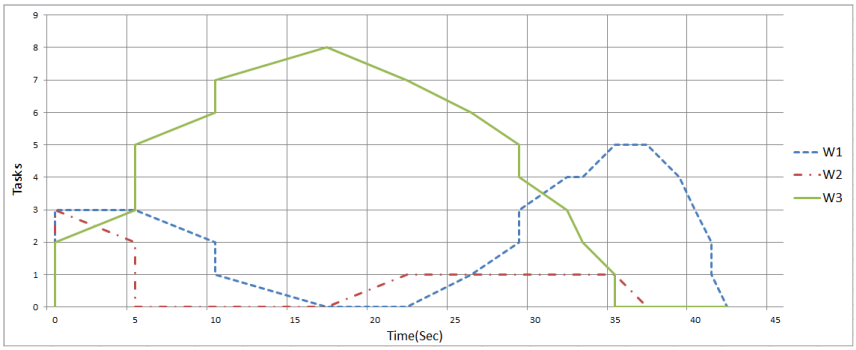
Figure 5.10: The mobility behaviour of 10 tasks on 3 workers(Matrix Multiplication)

For the Raytracer problem, we run with 8 tasks on 3 locations. The load is also generated by the load function but with more delay amongst the nodes; see Figure 5.11(a). The HWFarm scheduler produces dynamic schedules according to the load state of the nodes. Like the Matrix Multiplication example, the mobility of the tasks is also behaving inversely to the load on the hosted nodes; see Figure 5.11(b).

Consequently, in both experiments, the skeleton responds quickly to load changes.



(a) The load pattern applied to the skeleton



(b) The mobility behaviour

Figure 5.11: The mobility behaviour of 8 tasks on 3 workers(Raytracer)

5.4.2 Mobility Performance Validation

After evaluating the mobility behaviour, we need to run our mobile skeleton to explore how the skeleton improves the performance under loaded conditions. We run each experiment in three execution modes: the original mode (O), the load mode (L) and the mobility mode (M). In mode O, we measure the total execution time of running the problem with no load applied and no mobility supported. For mode L, we measure the times in the presence of the external load. In mode M, we measure the total execution times for running each problem with the presence of the external load while mobility is switched on.

To explore how mobility in HWFarm improves the execution time in the presence of the external load, we compare the execution times before and after applying mobility in modes L and M, respectively. Then we calculate the compensation by comparing the improvement when mobility is applied compared to the degradation of the execution time when the load is present, $Compensation(\%) = \frac{Diff(L\&M)}{Diff(O\&L)}$.

Table 5.12 shows the results of Matrix Multiplication. We can see how the

execution time becomes longer due to the load applied. Then, after mobility, we notice that the execution time is improved compared to the execution time without mobility. Here, the compensation is ranging from 12.41% to 57.52%.

Matrix Multi	Ts/Ws [a]	Mode O(S)	Mode L(S)	Mode M(S)	Diff[b] (O&L)	Diff[c] (L&M)	Improvement (%)
3600*3600	6/3	26.65	40.35	32.47	13.7	7.78	57.52
4800*4800	12/3	31.08	47.28	42.15	16.2	5.13	31.66
5600*5600	14/3	42.74	61.46	57.83	18.72	3.63	19.41
6000*6000	6/3	120.95	164.91	159.55	43.96	5.36	12.19
6000*6000	10/3	73.81	104.08	94.42	30.27	9.66	31.92
6000*6000	12/3	60.98	86.83	81.69	25.85	5.14	19.91
7200*7200	12/3	102.52	143.58	138.12	41.06	5.46	13.31
7700*7700	14/3	108.9	165.09	149.35	56.19	15.74	28.01

[a]The total number of tasks/workers
[b]The difference between mode O and mode L
[c]The difference between mode L and mode M

Table 5.12: The improvement in the performance in the presence of external load(Matrix)

For the Raytracer problem, we also run different number of rays with various numbers of tasks; see Table 5.13. Like Matrix Multiplication, we can see the improvement in the total execution time after applying mobility. The compensation in Raytracer is ranging from 23.91% to 59.09%.

As a conclusion, in both experiments, either with regular or irregular computations, the HWFarm skeleton seeks to improve the performance of the problem it runs when one or more of its nodes experience highly loaded conditions. Furthermore, these results show how our skeleton compensates for changes on the node's load. Our experiments suggest that the compensation can reach 59%. We should mention that this improvement mostly depends on the amount of load on the loaded nodes, when this load is applied, and how the local computations are affected by this load. Note that in the irregular computations the estimation is less accurate but the results show improvement in the performance when activating mobility.

Raytracer (rays)	Ts/Ws [a]	Mode O(S)	Mode L(S)	Mode M(S)	Diff [b] (O&L)	Diff[c] (L&M)	Improvement (%)
90	6/3	24.66	35.31	32.10	10.65	3.21	30.10
100	5/3	36.82	49.06	41.82	12.24	7.24	59.09
120	8/3	32.62	47.51	42.22	14.89	5.29	35.55
140	8/3	49.21	66.99	63.21	17.78	3.78	21.26
150	9/3	44.55	58.59	54.65	14.05	3.94	28.08
150	10/3	40.38	55.75	48.47	15.37	7.28	47.34
150	15/3	28.01	39.11	35.58	11.10	3.53	31.84
200	8/4	94.25	121.37	107.35	27.12	14.02	51.68
300	16/4	105.17	143.87	134.62	38.70	9.25	23.91

[a]The total number of tasks/workers
[b]The difference between mode O and mode L
[c]The difference between mode L and mode M

Table 5.13: The improvement in the performance in the presence of external load(Raytracer)

5.5 Summary

In this chapter, we demonstrated the scheduling approach used in HWFarm. The HWFarm skeleton uses a costed-informed scheduler to meet its performance goal, reducing the total execution time. This scheduler uses a circular mechanism to collect the load information from the nodes involved in running the skeleton. Next, this information will be delivered to the sender-initiated worker that needs it for making scheduling decisions. Then, the scheduler will reallocate the task based on the decisions made by the loaded workers.

We explored that the overhead in HWFarm is low compared to the total execution time. This overhead is incurred by the allocation, load diffusion, and mobility operations. Our experiments suggest that the overhead of the mobility activities is low even with the worst case scenarios when moving all local tasks. These experiments concluded that the total overhead of the skeleton activities is less than 0.6%. Furthermore, we demonstrated some procedures to optimise that overhead in the HWFarm skeleton.

Finally, some experiments have been carried out to evaluate this scheduler in terms of mobility behaviour and mobility performance. As a result, once some nodes

become loaded, this scheduler reduces the total execution time and compensates for the load changes.

In the next chapter, we present our load generator tool that we used to apply various patterns of load to the experimental nodes.

Chapter 6

Generating Load Patterns

In the previous chapters, we discussed the HWFarm skeleton and its dynamicity. Nonetheless, it is necessary to evaluate the scheduling decisions and policies produced by this skeleton under repeatable conditions. Typically, such parallel systems are evaluated on dedicated platforms with little or no external impact on load. For dynamic systems, however, such as those that adapt to changing conditions, it is necessary to generate both predictable and realistic patterns of load in order to mimic a real loaded environment. We have developed a novel load function which may be instantiated to generate dynamic, adaptive, predictable patterns of load across multiple processors. Our function can both generate idealised load patterns, and record and playback real load patterns. Furthermore, it can dynamically maintain a required load pattern in the presence of external real-time load changes, which makes it particularly suitable for experimentation on shared systems. In this chapter, we start with an introduction in Section 6.1. Next, in Section 6.2, we discuss the design of the load function and show that it can generate dynamic, adaptive and precise load, with minimal impact on system load. We then illustrate its use in the experimental evaluation of static/dynamic load balancing, load stealing and mobile skeletons in Section 6.3.

6.1 Introduction

In recent years, communication networks and computer environments have offered resources which are distributed across a large number of systems and are shared by a large number of users. The demand for resources in such computational environments is irregular, so the load may be unpredictable.

In real world systems, there is a fundamental difference in behaviour between dedicated systems, like supercomputers, where the parallel system is dedicated to execute the scheduled tasks, and non-dedicated systems, like servers, where multiple tasks can share the resources, thus the system may have volatile loads.

Heterogeneous architecture software needs to be tested and validated, but resource usage depends on the computing demands from other user processes. Thus, the experimental environment for such software needs to be adaptable to reflect changing conditions. Some simulation tools, for example SimGrid [53], can be used to explore varying loads. Nonetheless, simulating the interaction and behaviour of distributed system nodes is very difficult and may be impossible in some situations where it is very hard to obtain the influencing factors [41].

For better results, it is more efficient if these experiments run on real environments under controlled conditions. Thus, a load generator is needed to mimic such conditions by producing a desired amount of load across the environment. Ideally, the load generator would produce defined levels of load on CPU, memory, cache and network. For example, KRASH [182] is a tool for reproducible generation of system-level CPU load on many-core machines. It creates a dynamic and precise load but only for multicore systems. Stress [226] is a workload generator for stressing the CPU, memory, I/O and the disk. This tool spawns a fixed number of processes with some calculations for stressing the CPU. The load generated using this tool is non-dynamic where it is not changing at run-time. Another method presented by Makineni et al to reduce the CPU performance is down-scaling the CPU frequency which is used to reduce CPU power consumption [156]. Moreover, cpulimit [157] is a tool to limit the CPU usage of a process. It controls the CPU time dynamically and quickly without changing the scheduling settings but it does not handle multicore

systems. Wrekavoc [90] is a tool for heterogeneity simulation which enables users to limit the resources available to their application. Lublin et al [154] proposed an approach to instrument workload models of the system. This approach analyses and models the job-level workloads to substantially improve the experimental procedures.

In this chapter, we are exploring a mechanism to generate loads to degrade system performance on heterogeneous architectures and control the resource usage. We discuss the implementation of a load function which may be instantiated to apply dynamic, precise, adaptive patterns of load in a dedicated system to simulate different load scenarios that may occur in a shared distributed non-dedicated system. Our load function has been constructed to generate CPU load, as the CPU is a significant element in high performance computing. This function is able to generate a dynamic, precise and systematic load on shared/distributed memory architecture. Hence, we can prepare and replicate real experimental conditions by applying various patterns of loads. Moreover, the load function is able to measure and record the load for the whole system, nodes and cores, where it can use the load pattern later for mimicking the whole system. Generating loads for memory, cache and network are beyond the scope of this work.

6.2 Design and Implementation

6.2.1 Load and Scheduling

In this section, we propose the design and implementation of the load function that creates threads which are scheduled on a regular basis. The time slices assigned to these threads depend on the amount of load in the load pattern.

Our function has been designed to meet the following requirements:

- *Reproducibility*: The load function is able to generate the desired load on the system regardless of environmental conditions (number of machines, number of cores, other user processes).

- *Precise*: It can generate a precise CPU load through matching the given load

to the desired load.

- *Dynamic*: Under external real-time changes, a required load pattern can be dynamically maintained, which makes the load function specifically appropriate to be used in experimentations on shared systems.

- *Adaptive*: The load function is able to generate patterns of load considering the current load of the system. This also improves the precision of the generated load where other user's loads will be part of the given pattern of load.

- *Over-loading & Non Intervention*: The load function can create any number of loaders on a core, resulting in a highly loaded core. Furthermore, the load function has minimal impact on the system because the scheduling policy is not affected and the priorities of the current processes are not changed.

6.2.2 Load Function Design

The load function is designed using the Master/Worker model, see Figure 6.1. Here, the master is responsible for managing and controlling the workers which are distributed over all the nodes in the system, as localised measurement entities and load generators. The load function will run on multiprocessor systems where the master will be hosted on a node as the global controller while worker processes are distributed amongst the nodes. However, each worker process generates a thread, the local controller, and the load generator threads, the loaders.

The load function operates in two modes: recording the current load and generating load patterns. Accordingly, the global controller will maintain the desired operation through cooperating with the remote controllers. On other hand, the local controller is responsible for either recording the node load or generating the desired load on that node.

Generating load on a CPU means making it unavailable for processing other work. In other words, generating the CPU load involves creating and running threads/processes on the CPU cores. A loader is an intensive thread which runs

on one CPU core and has to be controlled to adjust the amount of load, either by the thread itself or by another thread, the local controller. This thread will run frequently to monitor and manage the loader threads with no change in their priorities. However, the frequency of running the local controller thread should be balanced to avoid extra load on the CPU and to precisely control the load. Our function runs with regular policy without changing any priorities.

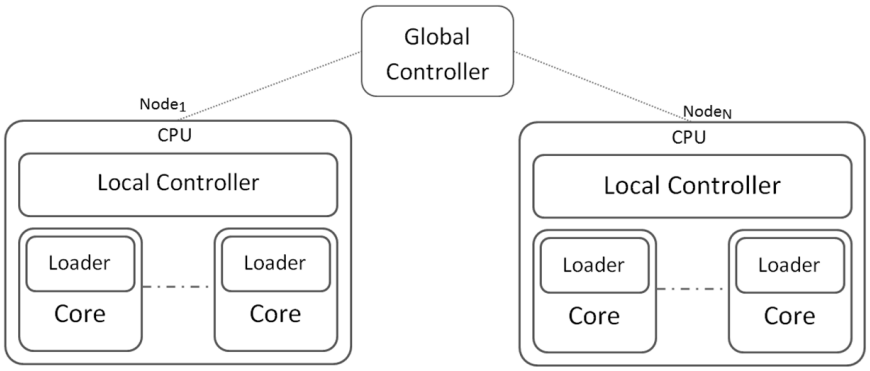


Figure 6.1: The load function design.

Typical parallel applications are composed of many processes or threads [120]. These threads use the CPU cores which are the smallest computing elements in a computing system. The operating system scheduler assigns a CPU core to threads. These threads are competing for accessing the core at the same time. Then, the scheduler has to choose which thread should run on the core using scheduling policy. The schedulers try to balance fairly resource usage amongst running threads. Therefore, the scheduler will use time-slicing by assigning time intervals of the core execution to all threads intend to run on the core where the time intervals assigned to the threads depends on their priorities and the scheduler policy. We can conclude that the core load is the ratio of unavailable time slices to the total time slices.

Applying a load on a core means making some time slices on the core unavailable. Regarding the dynamic load, the local controller will change the number of unavailable time slices in the core depending on the load profile. In contrast, for adaptive load, the local controller will take into account the current external real-time load changes and generate the remaining amount of load to reach the desired load.

Variants of load injector use a supervisor model, for example KRASH [182] and Wrekavoc [90].

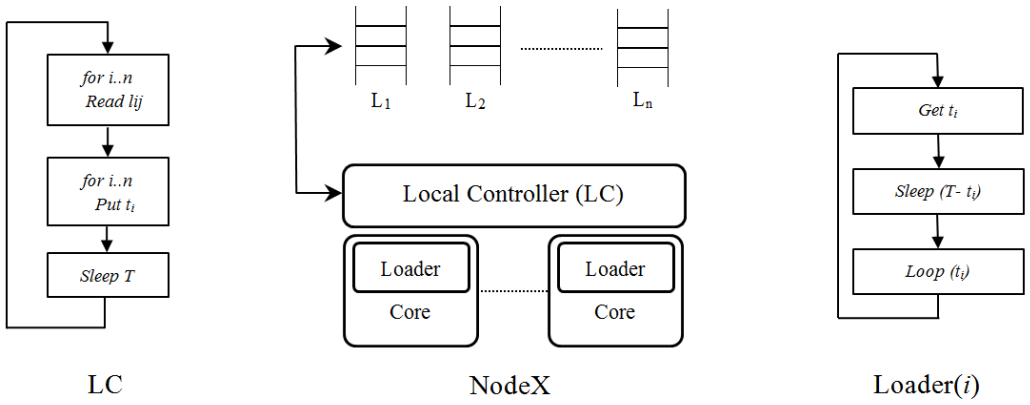
6.2.3 The Implementation

We implement our load function using C and MPI [206] while we use the PThreads library to create and manage the threads [48]. In this implementation, we target MPI compatible systems with Linux operating system (the Linux kernel is 2.6 or later). Here, the function has two main tasks: recording the loads of the machines and generating CPU loads.

To record the load, a monitor thread is created by the local controller to record all information about the machine using the `/proc` virtual file system. The information is collected every second by default, or according to input configurations. After that, the information will be sent to the global controller to create the load pattern for the current system.

To generate the CPU load, see Figure 6.2, the local controller will create a loader thread for each core in the hosted node. Thereafter, it will assign a core to a thread to guarantee that the thread is running only on one core. This is implemented using `cpuset`, a Linux feature which can be used to restrict the thread execution on a specific core or cores (in PThreads, this is implemented in thread affinity) [175]. Depending on the load pattern and for generating a precise load, the local controller will check frequently each loader to make sure that it is loading the core with the desired amount of load.

The loader thread is a simple infinite loop with conditions to keep the loader monitored and controlled by the local controller so that it has minimal impact on cache and memory. The local controller will run once per second by default, or according to input configurations. Each time, the local controller will calculate the amount of load for each loader depending on the load pattern and the actual load. Then, it sets the sleep period of the loader threads. Hence, the generated load will be precise and match the desired pattern of load. The local controller is not attached to a specific core so that it does not matter where it runs. If the scheduling is fair, the local controller will run on time.



L_i: The load pattern for a core.
n: Number of cores.
l_{ij}: The amount of load for the core i, at time j.
t_i: The amount of time to be spent at the core i.
T: The occurrence time.

Figure 6.2: The load function structure.

6.3 Load Function Evaluation

In general, the load function may change the loads of arbitrary processors across a cluster or Grid, according to the load pattern with which it is instantiated.

The load function was tested with a Beowulf cluster located at Heriot-Watt University. The cluster consists of 32 eight-core machines where each is an 8 core Intel(R) Xeon(R) CPU E5504, running GNU/Linux at 2.00 GHz with 4096 kb L2 cache and using 12GB RAM.

In the first experiment, see Figure 6.3, we validate the reproducibility for a real environment by running the LINPACK [86] benchmark over 4 nodes. First, we run the load function in the record mode to observe the load of the system. After that, we reproduce the recorded load pattern on the same nodes. The average error between the load pattern and the generated load is 0.62 sec with a standard deviation 0.105 sec.

To validate the dynamic and adaptive requirements, we propose a simple pattern of load. Here, during run-time the load function generates the load dynamically and matches the generated load to the given pattern of load. The load function can run in either adaptive or non-adaptive mode.

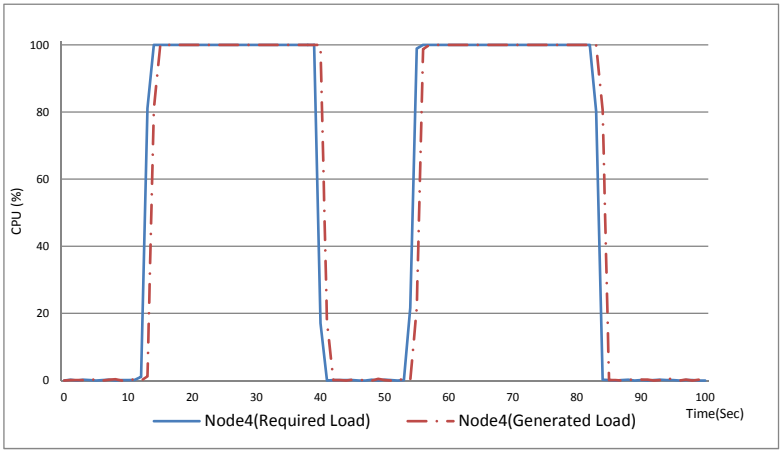


Figure 6.3: The required and actual load in node 4.

In adaptive mode the function will take into account the current system load while in non-adaptive mode it will generate the load regardless of the current load. In this experiment, we generate the load over 5 nodes with an adaptive mode. Surprisingly, an external user monopolises the first node for some time, see the green curve in Figure 6.4. In this case, the local controller in the first node will ask the loaders to reduce the artificial load to make the total load equal to the required load, see Figure 6.4. This will make the node loaded with the desired amount of load apart from how many users are using the current node. The generated load will be precise with a necessarily delay if the load of other users below the wanted load. Note that there are many saliences in the generated load. This happens when there are load changes on the system and the load function takes an action to adjust the generated load to match the desired value.

The more precise a load is generated, the better a real system is simulated. The local controller collects, generates and assigns the amount of load for a loader. Therefore, it is very important to run the local controller thread on time to set the required amount of load. See Table 6.1 which illustrates the average error for generating varying amounts of load under 100%. We run the load function in adaptive and non-adaptive modes. Here, we notice that the average error in the adaptive mode is around 0.18 at the low loads while in the non-adaptive mode the average error is around 0.2 at the high loads.

If the load is more than 100%, the local controllers will compete for acquiring

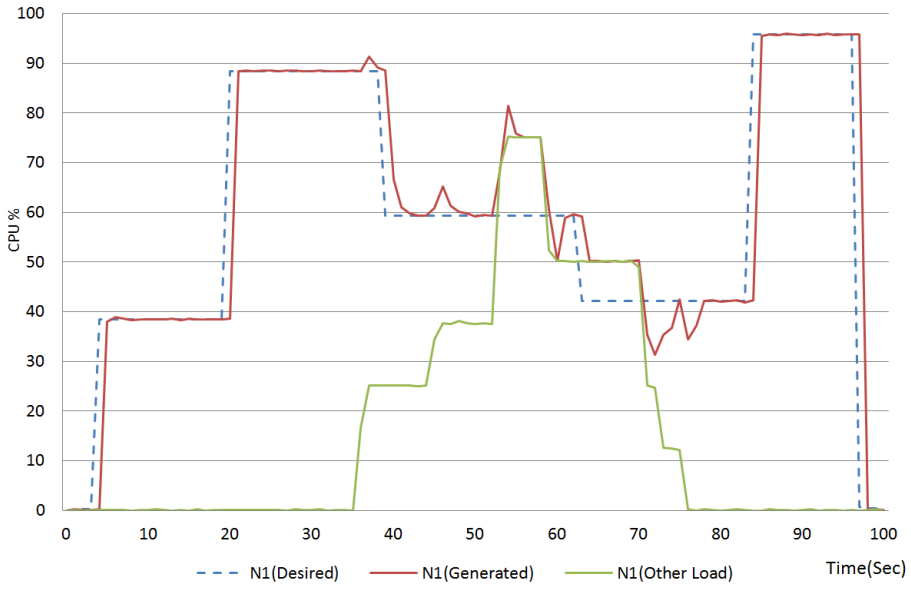


Figure 6.4: The required and actual load in the node with other changes in the load (adaptive mode).

resource. An undesirable delay in executing the local controller will occur which affects only the next time interval. This delay depends on the total number of threads and the scheduling policy. The delay will not affect the generated load if the required load is over 100% but if the load in the pattern decreases the load then a slight error may appear.

6.3.1 The Load Function Impact

When conducting an experiment, the load function runs at the same time to apply a load pattern for evaluating the solution. So it is important to ensure that running the function itself will not have a significant impact on overall system performance. To explore this, we use a Matrix Multiplication benchmark with the load function doing nothing.

As Table 6.2 shows, we found that the effect on the system with a load function doing nothing is from 0.05% to 0.87%. We conclude that the load function has an insignificant impact on the overall performance of the system.

Because we are working across distributed memory architectures, it is also very important to check the function's impact on network performance. However, the communications within the load function are performed only at the start-up and

Loads	Adaptive Mode		Non-Adaptive Mode	
	Average Error	S-Deviation	Average Error	S-Deviation
1 %	0.151	0.149	0.099	0.123
2 %	0.156	0.119	0.062	0.083
5 %	0.168	0.143	0.116	0.080
10 %	0.184	0.085	0.068	0.049
25 %	0.080	0.046	0.053	0.053
50 %	0.075	0.063	0.088	0.031
75 %	0.081	0.041	0.120	0.043
90 %	0.051	0.074	0.157	0.052
98 %	0.099	0.050	0.175	0.061
99 %	0.038	0.058	0.181	0.063
100 %	0.056	0.207	0.204	0.173

Table 6.1: The precision of load generation by the load function.

	1000x1000	2000x2000	3000x3000	4000x4000	5000x5000
Time	0.687	2.525	9.923	18.034	40.143
Time with the load function	0.693	2.527	9.963	18.043	40.363
Percentage	0.873 %	0.079 %	0.403 %	0.05 %	0.548 %

Table 6.2: The impact of the load function on the system.

the finish time. Therefore, the load function has a negligible impact on the network performance.

Regarding other impacts, such as memory and disk impacts, in this work, we are not addressing these impacts where we implemented the load function with minimal memory and disk access. We expect that the impact is negligible but this needs to be investigated.

Now, we explore the use of the load function in three parallel computing experiments. In this section, we do not address the evaluation of these experiments themselves; rather we are evaluating tool use in very different contexts to control resource availability according to a load pattern.

6.3.2 Load Balancing

Load balancing attempts to balance the work load of all locations in multicomputer systems [54]. In static load balancing, the work load is allocated at the start-up while in dynamic load balancing the work allocation depends on information

collected from the workers. Thus, the behaviour and performance of an experiment in load balancing depends on the current load of the system. We implemented a Matrix Multiplication benchmark using the Task/Farm model in static and dynamic mode. In the static version [200] the tasks should be distributed evenly amongst all the workers. For dynamic load balancing, the distribution of tasks depends on the internal and the external load of all workers [202]. Then, we run both implementations for a 6000x6000 matrix with 100 tasks over 5 nodes alongside with the load function with a load pattern illustrated in Figure 6.3 only for the first 3 nodes.

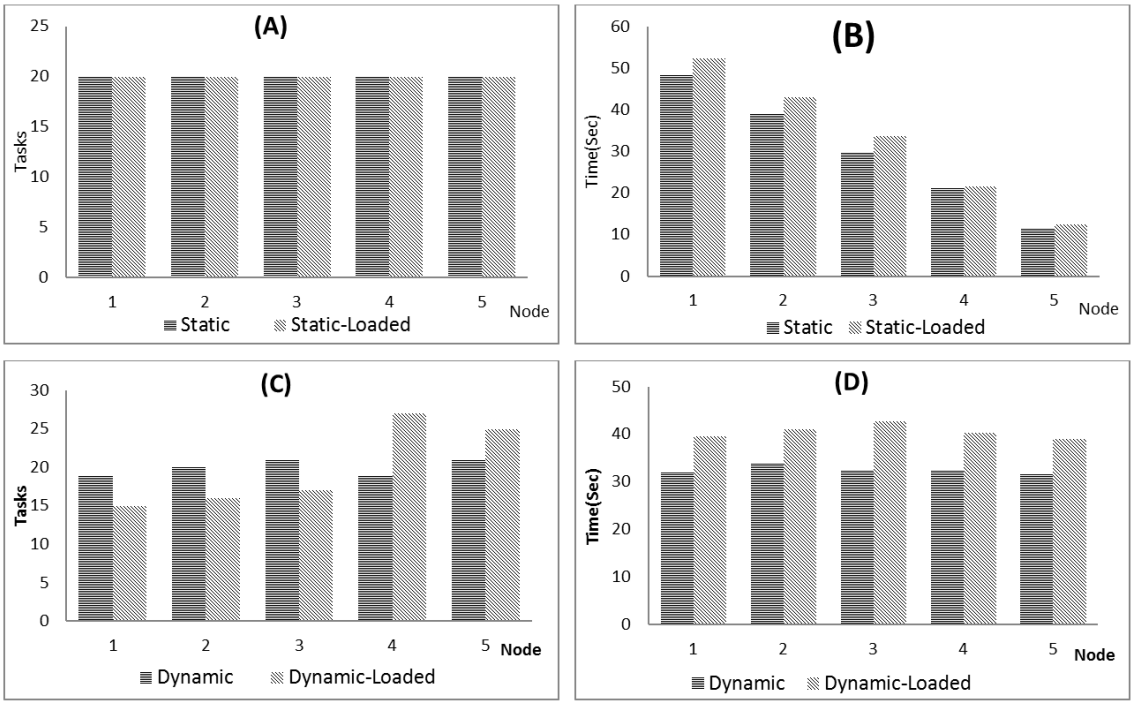


Figure 6.5: Load balancing (static/dynamic) under load changes.

Figure 6.5 presents the results of running 100 tasks over 5 nodes. In static load balancing, the tasks are evenly distributed amongst all nodes, both the loaded and unloaded; see Figure 6.5 (A). But, the loaded nodes take longer times to finish executing the tasks allocated to them; see Figure 6.5 (B).

In the dynamic version, Figure 6.5 (C) shows that the number of tasks allocated to nodes is varied depending on the load state of the nodes. Figure 6.5 (D) illustrates that the time to complete all running tasks is roughly the same on all nodes.

In the load balancing experiments, it can be observed that the generated load has a direct impact on the behaviour of such experiments. Consequently, such a tool can create a realistic loaded environment to help in evaluating these experiments.

6.3.3 Work Stealing

Work stealing is a thread scheduling technique for shared-memory multiprocessors where a thread steals works from other threads [38]. For this experiment, we use one node which has 8 cores. We run 8 threads over 8 cores where each thread has a pool of tasks and these pools are shared amongst all threads. We repeated the running 9 times with changing the number of loaded cores through assigning cores to loaders.

Tasks on	Number of Loaded Cores								
	0	1	2	3	4	5	6	7	8
Core 1	256	**166**	**158**	**146**	**128**	**147**	**171**	**205**	**256**
Core 2	256	269	**160**	**149**	**128**	**146**	**171**	**205**	**256**
Core 3	256	269	290	**149**	**128**	**146**	**170**	**205**	**256**
Core 4	256	269	289	319	**128**	**147**	**171**	**206**	**256**
Core 5	256	269	288	320	384	**146**	**171**	**205**	**256**
Core 6	256	269	287	322	383	438	**171**	**205**	**255**
Core 7	256	269	289	321	384	439	511	**206**	**257**
Core 8	256	268	287	322	385	439	512	611	**256**

Table 6.3: Work Stealing with the number of tasks processed on each core (bold number refers to the number of tasks processed on a loaded core)

Table 6.3 illustrates the effect of changing the load on task distribution. Here, the tasks should be evenly distributed amongst the cores if they have the same amount of load. In the table, bold numbers refer to the number of tasks processed on each loaded core. We can see that as more as cores are loaded, the tasks are redistributed to maintain overall balance between loaded and unloaded cores. Note that when the number of loaded cores is 7, this makes the 8th core execute more tasks compared with the other loaded cores.

Like load balancing, the load function provides a mechanism to evaluate the work stealing experiments.

6.3.4 Mobility

Next, we consider a mobile skeleton for a Raytracer benchmark that generates the image for 100 rays for 120,000 objects in a 2D-scene. This skeleton is executed over two nodes to execute the benchmark composed of one task.

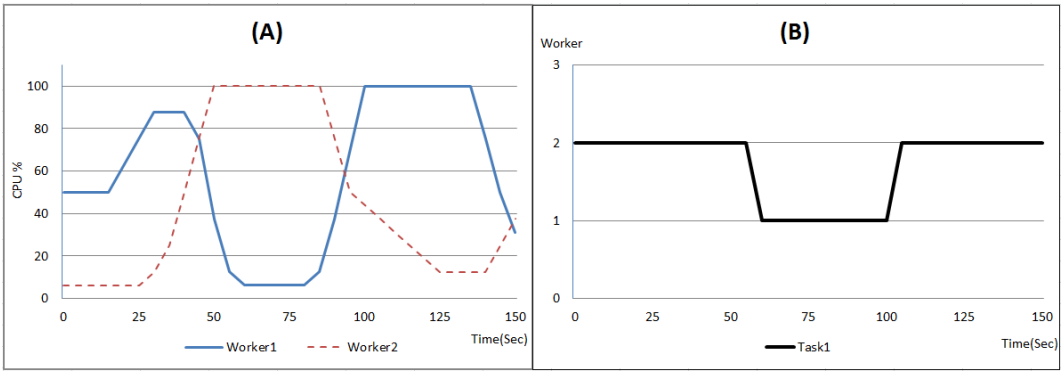


Figure 6.6: The load pattern applied to Raytracer and its impact on moving tasks between workers.

Figure 6.6 (A) shows the applied pattern of load while Figure 6.6 (B) gives how the task changes its location according to the load state of the worker. The decision of moving the task has been taken by the skeleton which mainly depends on the load on the current worker and the other workers.

Like load balancing and work stealing experiments, this experiment shows the effect of the generated load on the skeleton behaviour.

6.4 Summary

We have presented a new tool that generates dynamic, precise, adaptive CPU load. This tool helps in evaluating experiments that depend on changes in the load in multi-processor and multi-core environments. This tool is implemented as a load function which we have shown to have minimal impact in an experimental setting. Overall, we can conclude that the load function is highly effective in a dedicated system for simulating patterns of load changes in a shared system.

We think that our load function is of far wider applicability. For example, it might be used in a homogeneous setting to simulate a heterogeneous environment

by giving differential constant loads to the processing elements with the same characteristics. It might also be used to simulate different patterns of system component failure by giving processing elements infeasibly large loads.

Chapter 7

Evaluation

In this work, we propose a load-aware skeleton used to solve problems through exploiting shared parallel computing platforms. Here, we will discuss how our skeleton can be used to solve different types of problems in many different areas as well as running large scale problems. This enhances how our skeleton is capable of accommodating diversity, which is one of principles in designing skeletal-based systems. Furthermore, we will explore one of the side effects of our skeleton behaviour through investigating the effect of mobility on other applications running on shared nodes. In this chapter, we start with an introduction in Section 7.1. Next, in Section 7.2, we evaluate the usability of HWFarm by applying it to pipeline structures. Then, we evaluate scalability by measuring runtime on large architectures in Section 7.3. Most importantly, we evaluate adaptivity by measuring the runtimes of applications competing for resources on a small cluster in Section 7.4.

7.1 Introduction

Parallelism with high performance computing has introduced techniques to solve complex problems that were not manageable on single processors. These techniques have been implemented in many different areas: finance and trading, climate research, and biosciences. To put our skeleton in the right context, it should be able to solve problems related to data science such as modelling and numerical simulations. Here we will demonstrate three of the common problems in data sciences: the

N-body simulation problem, the BLAST algorithm and the findWord problem.

The N-body problem is a numerical simulation for motion of N particles that are interacting gravitationally [218]. N-body algorithms have a wide range of applications such as plasma physics and molecular dynamics. The simulation of the movement of each particle is distributed over time-steps. Each step requires computing all forces exerted on each particle and then updating the new locations and the new velocities for all particles. At each time-step, $O(N^2)$ operations need to be computed. The pseudo-code of the sequential version of this problem is:

```
Set initial positions for all particles
for each timestep do
   for each particle j do
      for each particle i do
       calculate the force at particle j
      update the velocity and the location of particle j
   endfor
endfor
```

BLAST (Basic Local Alignment Search Tool) algorithm is used to search for sequences in a database of DNA or proteins [17]. A parallel version of Blast has been presented in [144]. This algorithm is used to compare a database of sequences (biological sequences such as amino-acid sequences or DNA sequences) for detecting sequences above a concrete threshold. The pseudo-code of the sequential version of this algorithm is:

```
Set the query sequence
Make a k-letter query word list
Scan the database to find the list of matching words
Extend the exact match to High Scoring Pairs
Evaluate the score of High Scoring Pairs
Show the gapped local alignment
Report every match whose score is lower than a threshold
```

The findWord problem is a simple example of processing and analysing a huge amount of data. These data are stored in a large number of files located in a shared or distributed data storage. This problem has many applications such as natural language processing and text mining [135]. The pseudo-code of the sequential version of this problem is:

```
Read data from files
Extract the data
Analyse the data
Print out the results
```

All measurements are performed on local machines at Heriot-Watt University Edinburgh. Details about the machines are outlined in Section 5.3. Now, we will discuss some features that are considered in the HWFarm skeleton.

7.2 Parallel Pipeline

A pipeline is a form of parallelism composed of a sequence of stages that process a sequence of input [66], see Figure 7.1. When using skeletons, each stage of the pipeline can be executed by a skeleton to achieve the needed goal, see Figure 7.2. The pipelining approach is not directly implemented in HWFarm but if we assume that each skeleton call is a 1-stage pipeline then a sequence of calls yields a pipelined implementation. Here, we study the pipeline structure to extend the range of programs that can be solved using the HWFarm skeleton.

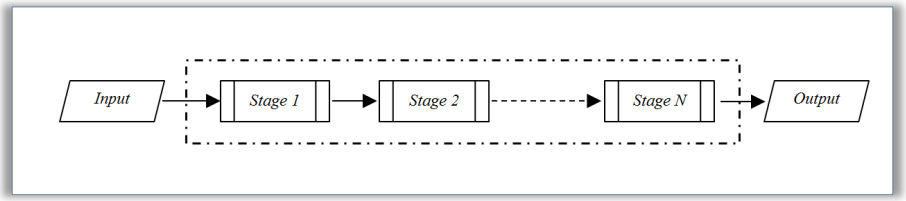


Figure 7.1: The pipeline approach.

To demonstrate a pipeline pattern using HWFarm, we use the problem of finding the most frequent word in a list of files, findWord problem. This example is composed of two functions, extracting the data from the files and finding the words in

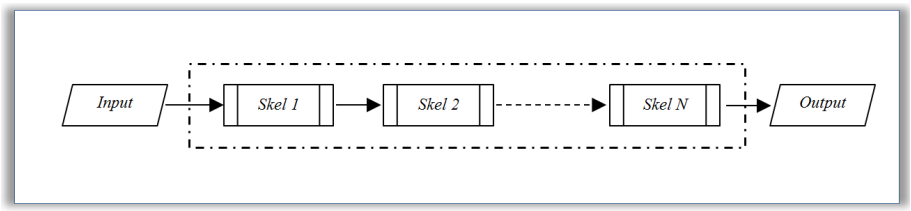


Figure 7.2: Parallel pipeline with skeletons.

the extracted data, see Figure 7.3. This problem represents irregular compunctions as the size of the files are variable. Furthermore, the size of the computation is large.

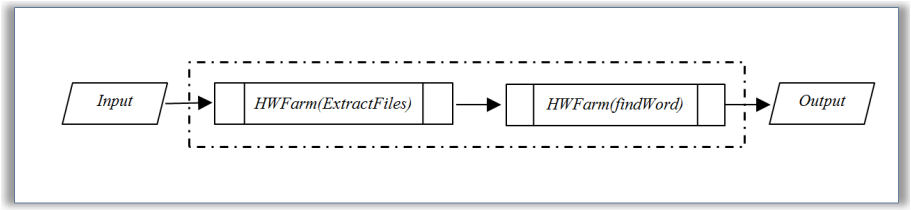


Figure 7.3: The structure of the HWFarm skeleton to solve a findWord example.

This experiment is performed in a Beowulf cluster at Heriot-Watt University over 30000 files stored in a shared storage where a Network File System is set up. In this example, there is no sending of the data between the master and the workers where we assumed that the files are accessible by all nodes.

Now, we run a findWord problem with two stages using 4 workers and 20 tasks as we need to distribute the files evenly amongst the workers. In the first stage, each task processes 1500 files and produces extracted data saved into files. Then, the second stage processes the extracted data for all files to find the most frequent word.

Figures 7.4, 7.5, 7.6 and 7.7 show the changes on the load over the 4 nodes, the top figure, and the behaviour of the tasks during their executions on that node, the bottom figure. These load patterns have been generated using the load function proposed in Chapter 6. This behaviour is influenced by the current load of the nodes. It can be seen that the HWFarm scheduler lightens the loaded nodes whenever the worker becomes loaded.

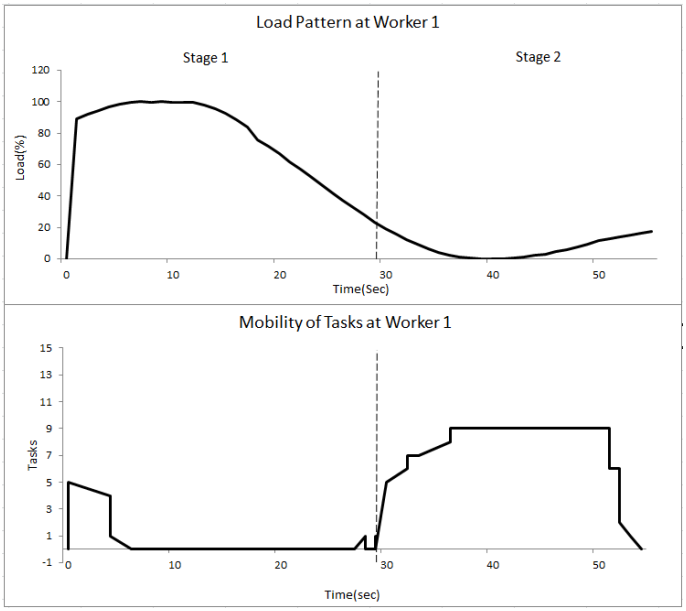


Figure 7.4: The load pattern and the mobility behaviour of tasks at at Worker 1.

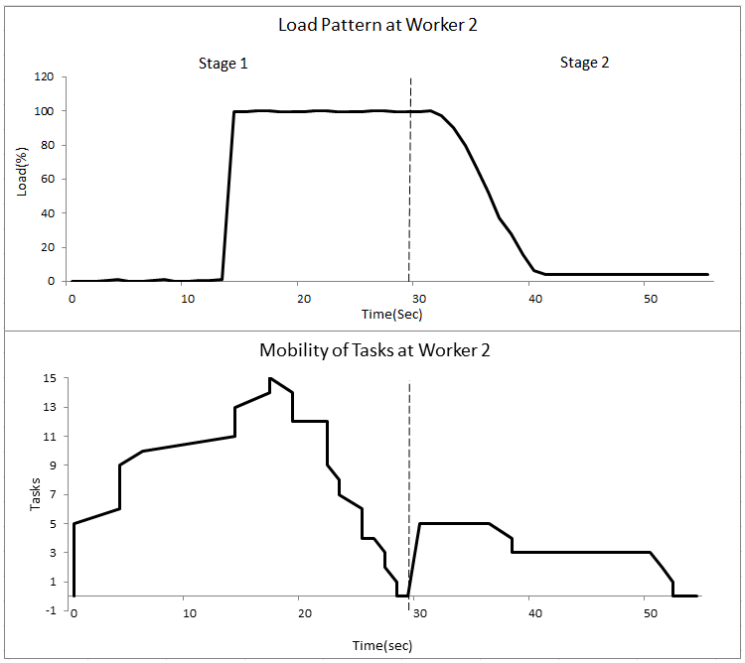


Figure 7.5: The load pattern and the mobility behaviour of tasks at at Worker 2.

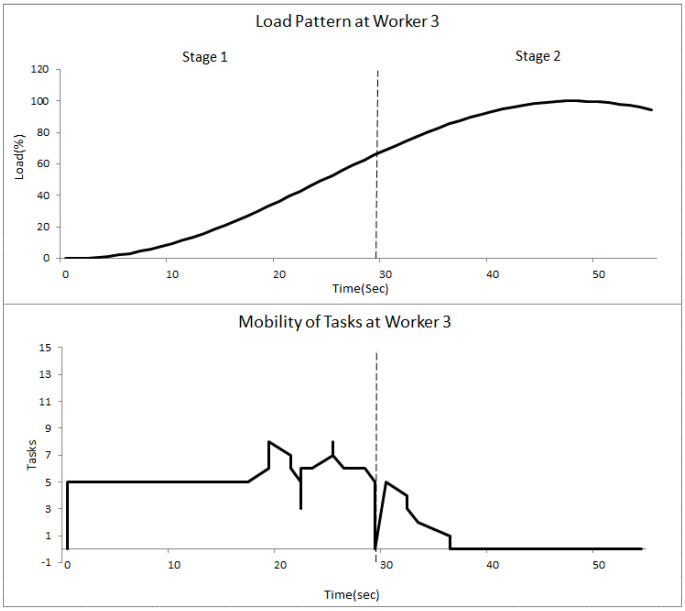


Figure 7.6: The load pattern and the mobility behaviour of tasks at at Worker 3.

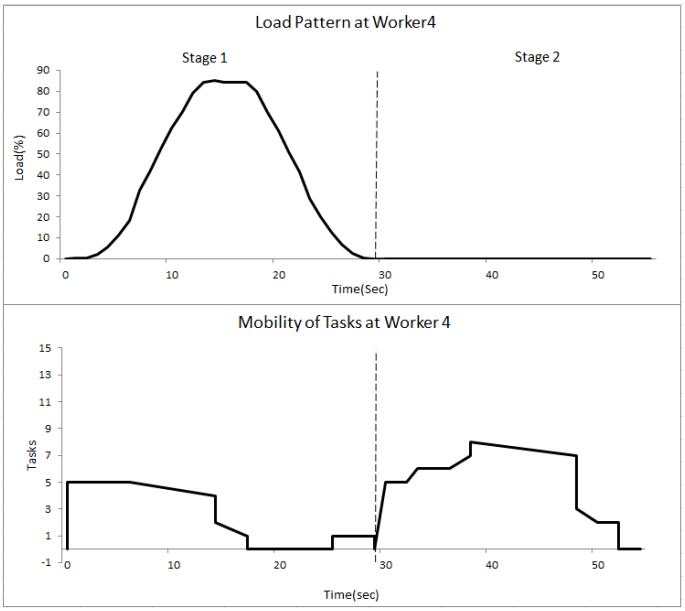


Figure 7.7: The load pattern and the mobility behaviour of tasks at at Worker 4.

During runtime, each task will be moved multiple times as long as the host worker is loaded. Because in this experiment, there are two stages with two skeleton calls, this means that each task will end its execution at the end of each stage. Hence, a new task distribution occurs at the beginning of each stage. Nonetheless, each task may be moved while executing a pipeline stage due to loaded conditions during this stage. Figure 7.8 shows task 1 and the workers which this task has visited during its lifetime. Here, task 1 has 2 movements in stage 1 while it has no movements in stage

2. Furthermore, Figure 7.9 shows the execution of task 7 which has 1 movement in stage 2 and 1 movement in stage 2.

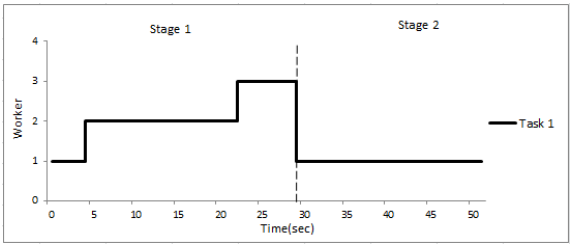


Figure 7.8: Task 1 and its locations in the findWord problem.

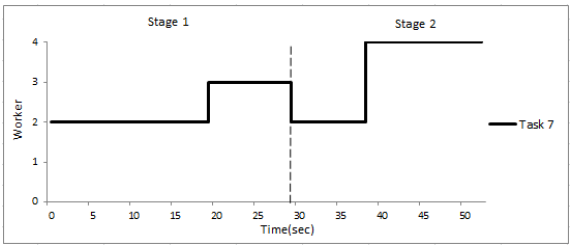


Figure 7.9: Task 7 and its locations in the findWord problem.

7.3 Scalability

This section discusses the scalability of the HWFarm skeleton over parallel computing architectures. We will measure the runtimes of running large-scale problems using HWFarm over a big number of nodes. Here, speed-up evaluation is not addressed in this work.

During the design of HWFarm, several issues have been considered to support scalability, such as:

- *Making the mobility decision*: The decision in HWFarm is taken through a decentralised approach where each worker is responsible for the decisions to move its tasks.
- *Transfer policy*: We used a sender-initiated mechanism where the loaded worker only triggers for mobility.

- *Load information*: A circulating method has been used to collect the load from the workers. This method has a light weight overhead, see Chapter 5.

Scalability is an important attribute in designing parallel algorithms and high performance architectures [213]. Therefore, scalability is subject to the implementation, data size and the available resources. The data size is very important because the structure of the skeleton at the master limits the data size to fit the memory of the master node. The communication latency also should be considered at the beginning, while during runtime the network latency is considered in the HWFarm cost model.

A first example of scalability is the findWord problem. In this experiment, we have 50000 text files. The skeleton will use 20 nodes as workers: 18 nodes with 8 cores on a Beowulf cluster, a 24-core node and a 64-core node. This problem can easily be scalable as the input is only the files needed while all data will be processed locally at the nodes. Figure 7.10 shows the execution times of running only this problem without background load. Each worker will execute one task or more if the number of tasks is greater than the number of workers. Each task will be allocated locally to a core if the node is not loaded.

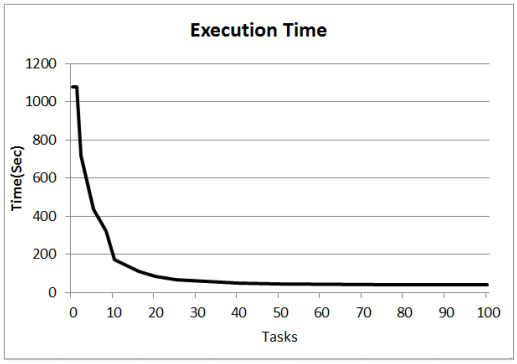


Figure 7.10: The execution times of running the findWord problem using the HWfarm skeleton.

Note that the total overhead is due to the implementation of this problem and the latency of accessing the files.

The second example is a numerical simulation for motion of N particles, the N-body problem. In this experiment, we used 100000 particles for 10 time-steps. Moreover, we used 21 nodes: 1 as a master and 20 nodes as workers.

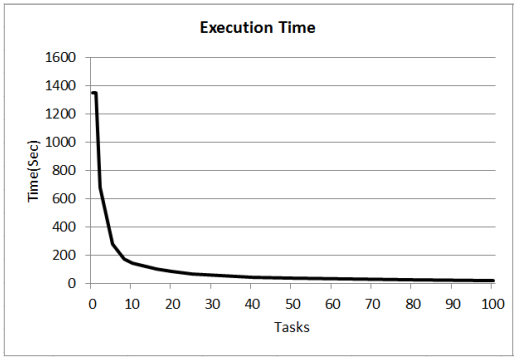


Figure 7.11: The execution times of running the N-body problem using the HWfarm skeleton.

Figure 7.11 illustrates the execution time of running only this problem with different number of tasks. Each task runs on a core and hence 100 cores are allocated to solve this problem. In this implementation, there are different sources of overhead such as communication and memory overhead.

As a conclusion, the HWFarm skeleton, static or mobile, can efficiently execute large scale problems over a big number of nodes without background load. This supports flexibility of the skeleton in solving different types of real algorithms, although there are some requirements to run the sequential code. This also enhances the skeleton in accommodating diversity which is one of the principles presented by Cole [67] to design skeletal-based systems.

The total overhead of any problem is due to the implementation, the nodes, the communication latency, and memory/storage overhead as well as the low overhead of the skeleton itself. In Chapter 5, we showed that the HWFarm skeleton has low overhead compared to the total execution time.

7.4 Adaptivity

In the previous experiments, we evaluated the HWFarm skeleton in the perspective of a user application running in parallel over a number of nodes. Also, we showed how the skeleton is adaptive to the load state of the system. Here we will discuss the side effect of this adaptivity on the system and on other applications sharing the resources with the skeleton.

To study the effect of adaptivity on the system and on all applications running on the system, we simulate resource contention occurring on a node by running three parallel applications at once on a specific node. These applications will compete for the node resources and therefore a delay may occur for all these applications. Here we are not using our load generator function because we need real applications running along with the skeleton to measure the execution times for all these applications. To demonstrate that effect from different angles, we run three instances of the skeleton executing three problems: BLAST algorithm, the N-body problem, and Matrix Multiplication. Each time, we activate mobility on an instance and disable it on the others. Disabling mobility makes the skeleton run as a parallel application composed of concurrent threads. Therefore, each instance of the skeleton will consider the other two applications as an external load. Thereafter, we will use B for the HWFarm (BLAST) skeleton, P for the HWFarm (Particles) skeleton, and M for the HWFarm (Matrix) skeleton. These applications are composed of different numbers of tasks. See Table 7.1 that shows the sizes and the number of tasks of these applications.

	Tasks	Size
P	5	100000 particles/ 1 time-step
B	4	50 million DNA genes
M	6	6000*6000

Table 7.1: The sizes and number of tasks of some applications.

We have 5 executing cases illustrated in Table 7.2. First we need to measure the original execution time for each application, case AAA. Next, we run all applications together with disabled mobility and measure the times for all these applications, case AllOff. Then, we run an instance of the skeleton with activated mobility while the other instances have disabled mobility for the problems P, M and B in cases POn, MOn and BOn, respectively.

To set up this experiment, we use three nodes of a Beowulf multicore cluster, a master and two workers; details about these nodes are outlined in Section 5.3. In case AAA, each application runs on one worker to measure its execution time. The number of tasks for each skeleton is less than the number of cores on that worker so no need for other workers. For the other cases, we use two workers because we

need to keep one available worker in case there is a need to move tasks to a new location when mobility is activated. We use only two workers because it is easier to demonstrate the results and show the movement behaviour of the skeletons at the run-time. Initially, all tasks of the three applications start at worker 1. Then, based on the load state, mobility occurs for the tasks of the skeleton that has activated mobility. In summary, our set-up shows that performance improvements are due to mobility and not additional cores.

Case	workers	P	M	B
AAA	1	alone	alone	alone
AllOff	1	Mobility Off	Mobility Off	Mobility Off
POn	2	Mobility On	Mobility Off	Mobility Off
MOn	2	Mobility Off	Mobility On	Mobility Off
BOn	2	Mobility Off	Mobility Off	Mobility On

Table 7.2: The cases of running the HWFarm problems.

Table 7.3 summarises the results of all executing cases. In this table, each line represents a case. In column Exec, each value represents the measured execution time of running an application(col) in a case(line). The Diff columns in case AllOff refers to the difference between the execution time in case AllOff and the execution time in case AAA. This shows how each application is affected by other applications. The Diff columns in cases POn, MOn and BOn, point to the difference between the execution time in that case and the execution time in case AllOff. The compensations from mobility compared to the times with high background load are shown in the Comp columns. Further details about those cases are as follows:

Case	P			M			B		
	Exec(S)	Diff(S)	Comp(%)	Exec(S)	Diff(S)	Comp(%)	Exec(S)	Diff(S)	Comp(%)
AAA	108.711			119.388			60.538		
AllOff	187.977	+79.266		218.714	+99.326		142.287	+81.749	
POn	110.378	-77.599	**97.90**	158.732	-59.982	**60.39**	116.969	-25.318	**30.97**
MOn	114.268	-73.709	**92.99**	122.188	-96.526	**97.18**	94.749	-47.538	**58.15**
BOn	162.945	-25.032	**31.58**	181.539	-37.175	**37.43**	62.911	-79.376	**97.10**

Table 7.3: Summary of the execution times and the improvements for all applications.

Case AAA

In this case, each skeleton runs alone where its tasks are executed on one worker. As a result, the measured total execution times are: 108.711 sec for P, 119.388 sec for M, and 60.538 sec for B.

Case AllOff

We will run all skeletons together where all tasks will start executing on the same worker, worker 1. In this experiment, all skeletons have disabled mobility and hence worker 2 will be idle. Figure 7.12 shows the number of tasks running of worker 1 for each application.

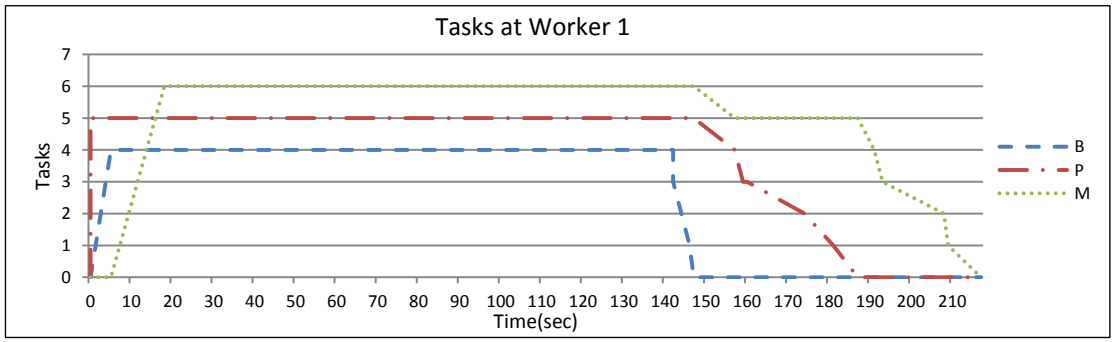


Figure 7.12: Mapping the tasks on worker 1 for case AllOff.

A delay will occur for all applications where worker 1 has only 8 cores while the number of tasks at some points is 15 tasks. Consequently, P takes 187.977 sec, M takes 218.714 sec, and B takes 142.287 sec. By comparing these times to the times in case AAA, the execution times of these applications have been increased by: 72.91%, 83.20%, and 135.04% for P, M and B respectively.

Case POn

In this case, we will turn mobility on for the HWFarm (P) skeleton to examine the improvement of total execution time for this skeleton and other running applications.

Figure 7.13 shows that all tasks of the HWFarm (P) skeleton are moved to worker 2 as worker 1 experiences increased load from the other applications. Therefore, P takes 110.378 sec, M takes 158.732 sec, and B takes 116.969 sec. By comparing

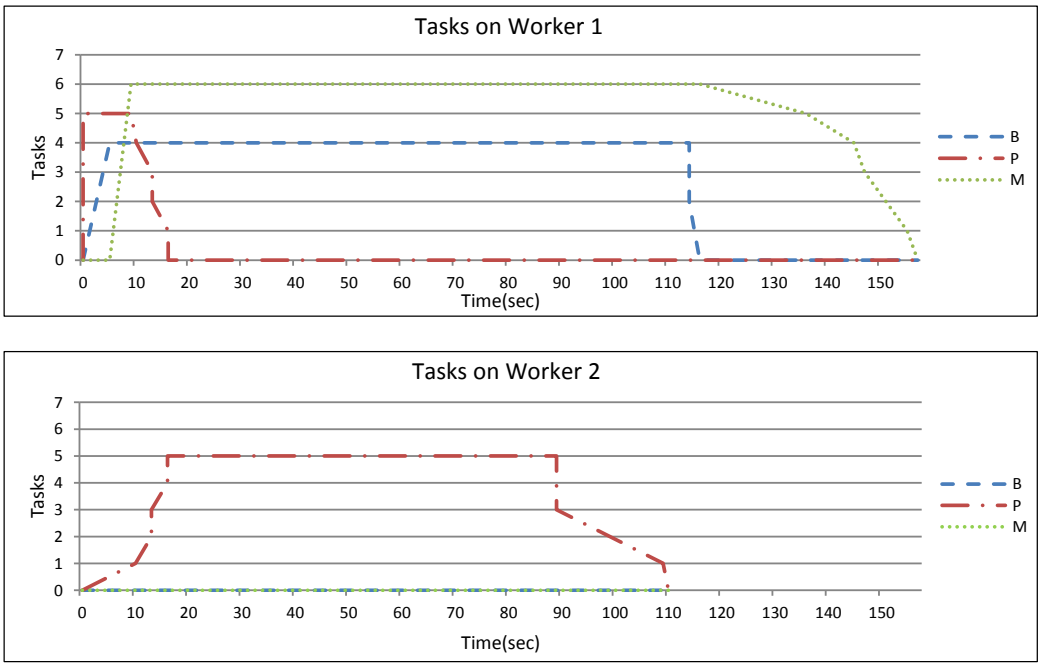


Figure 7.13: Mapping the tasks on worker 1 and worker 2 for case POn.

these times to the times in case AllOff, we can observe that this mobility decreases the delay due to the load where the execution time of the HWFarm (P) skeleton has been improved by 77.599 sec. Therefore, the movement of the tasks of P produces a large improvement and compensates for the loaded condition in worker 1 where the compensation for P is : $77.599/79.266 * 100 = 97.90\%$. Furthermore, this mobility reduces the resource contention on worker 1 and hence other applications will acquire more computing resources. As a result, the compensations for other applications, M and B, are 60.39% and 30.97%, respectively.

Case MOn

In case MOn, the HWFarm (M) skeleton has mobility turned on while all applications run on worker 1. Like case POn, a large improvement has been gained due to moving the 6 tasks of M to worker 2, see Figure 7.14. As a result, P takes 114.268 sec, M takes 122.188 sec, and B takes 94.749 sec. Here, the compensations are 97.18%, 92.99%, and 58.15% for M, P and B, respectively.

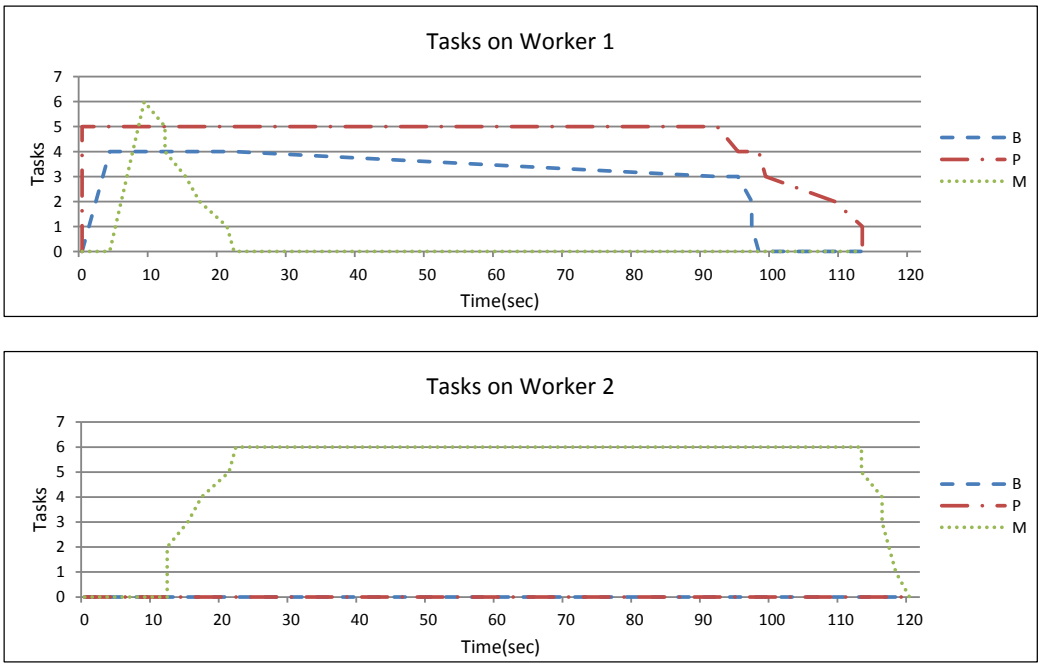


Figure 7.14: Mapping the tasks on worker 1 and worker 2 for case MOn.

Case BOn

In case BOn, the HWFarm (B) skeleton has mobility turned on where all applications run on worker 1. Like case POn and MOn, an improvement has been gained due to moving the tasks of B to worker 2. As a result, P takes 162.945 sec, M takes 181.539 sec, and B takes 62.911 sec. Here, the compensations are 97.10%, 31.58%, and 37.43% for B, P and M, respectively. See Figure 7.15 that shows the movements of the tasks of B.

According to these results, we can conclude that adaptivity improves the execution time of the skeleton and the execution times of the applications sharing the system resources. Our experiments showed that the direct compensation is larger than indirect compensations. This adaptivity also reduces resource contention and compensates for the loaded conditions. These improvements vary and are related to the number of movements and how the running applications are affecting each other. Moreover, another side effect of adaptivity is enabling the system to run applications faster and therefore improves the throughput of the whole system.

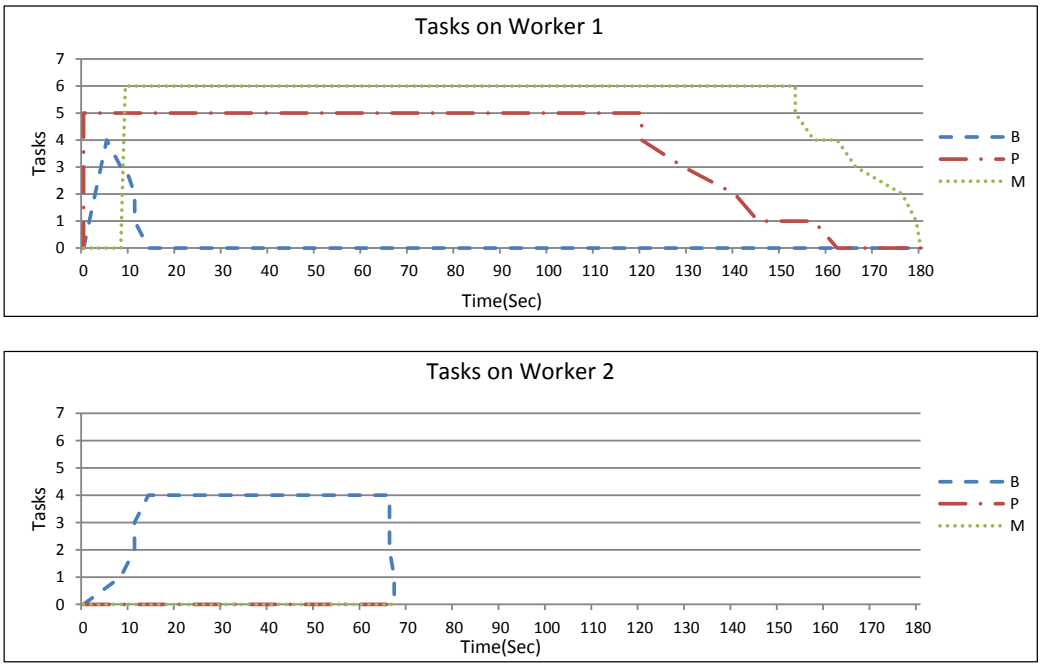


Figure 7.15: Mapping the tasks on worker 1 and worker 2 for case BOn.

7.5 Summary

This chapter includes many issues that are considered in HWFarm. We demonstrated how the HWFarm skeleton accommodates diversity through executing problems implemented using a parallel pipeline approach and running large scale problems. Furthermore, our experiments suggested that adaptivity of our skeleton compensates for the loaded conditions on shared platforms and reduces resource contention. Our experiments showed that the compensation may reach up to 92% compared to the time under a high background load. Moreover, we showed that a side effect of the adaptivity of the HWFarm skeleton is improving the throughput of the system.

Chapter 8

Conclusion and Future Work

8.1 Summary

Multicore clusters have emerged providing high performance computing platforms for running applications. Sharing the resources of parallel platforms amongst the applications demanding computing power leads to resource contention amongst these applications. This thesis presents the design and implementation of a skeleton (pattern) that seeks to find better locations for its computations taking into consideration the load variation and resource contention in shared multicore clusters. This pattern offers an efficient way to run algorithms and solve problems through exploiting parallel platforms when an external load is present. This pattern is implemented using skeletal-based approach which hides parallel details to keep the developer focused on the domain issues.

Chapter 2 provides the concepts related to parallel computing, cost modelling and scheduling. Furthermore, a survey of skeletons and parallel programming languages that support the skeletal approach has been introduced.

Chapter 3 proposes the design and implementation of the HWFarm skeleton. Moreover, this chapter gives a detailed description of the skeleton structure and how it can be used to run algorithms. This skeleton is proposed in two modes: static, where the skeleton allocates tasks to the nodes and waits until they finish their execution, and mobile, where the skeleton can move tasks amongst locations. This chapter explores how this mobility feature is implemented in the skeleton to enable it

to reallocate its tasks based on the system load state. This skeleton is implemented in C and runs over distributed and shared memory architectures. To support these architectures, we use the MPI and PThreads libraries. We also provide examples about how to run problems using the skeleton with guidelines on how to refactor the sequential code with following some restrictions. An example of these restrictions is loop parallelism as the program pattern where this skeleton supports running problems with index-based loops, outlined Sec 3.2.4.5. Moreover, the data defined by the user should be configured and allocated in consecutive memory locations. Also, pointers should be used in updating the output and state data. To support mobility, there are some considerations outlined in Sec 3.2.4.4. Furthermore, we assumed that the tasks are fixed length and the task pool is static. Also, the skeleton does not support adding or removing resources during the runtime and the tasks are independent with no communications. As a skeletal-based system, the HWFarm skeleton is evaluated in meeting the principles proposed by Cole [67] and Danelutto et al [72].

Chapter 4 introduces the dynamic, measurement-based cost model used in the HWFarm skeleton. This cost model is embedded in the skeleton to take the costed decisions needed for rescheduling the tasks. This model calculates the estimated continuation times for the current tasks in the local/remote nodes. These estimates help to find faster locations for the slow tasks. The concept used to estimate the continuation time is based on the measurement of the partial execution of the current tasks. Furthermore, this model calculates the mobility cost for moving a task between two nodes. This cost considers the network delay, the task size, and the load state of the system.

This chapter also describes in detail the parameters used by the HWFarm cost model. There are static and dynamic parameters. The static parameters, the CPU core clock speed and the number of cores, reflect the computing power of the nodes that host the skeleton tasks. In this work, we assume that the cores of a node have the same clock speed. The dynamic parameters used in the cost model are the number of processes and the CPU utilisation. Dynamic parameters from the

running computations are also used. In the mobility cost estimation, network delay is used as network metric.

Moreover, this chapter shows experiments on validating the decisions taken by the HWFarm cost model. These experiments demonstrate that the cost model gives accurate decisions under different load conditions for regular and irregular computations. In regular computations, our experiments show the accuracy of the cost model decisions with maximum error 3%. For irregular computations, the estimates are less accurate, as expected, with error reaching 20%. Regarding estimating the mobility cost, the error in the estimation is ranging from 0.1% to 25% where the actual mobility cost is relatively small.

This cost model uses these estimates to take mobility decisions. Therefore, validating the mobility decisions is also investigated in this chapter. Our experiments suggest that mobility decisions compensate for the loaded conditions by 75% and 90% for regular and irregular computations, respectively. These compensations depend on the load pattern applied and the number of tasks affected by that load.

Chapter 5 proposes the load scheduler used in the HWFarm skeleton. Moreover, this chapter explores the load information diffusion approach used in this scheduler. In this approach, the HWFarm skeleton uses a centralised mechanism to collect the load information of the nodes where the latest load information will be stored at the master.

Moreover, this chapter explores the policies used to trigger the mobility operations based on estimations of remaining work. These operations are triggered by the worker which is responsible for applying the cost model to calculate the required estimates and to produce the move report accordingly. Then, upon confirmation, mobility occurs for the selected tasks to the chosen workers. It is important to note that in HWFarm, the decision making is decentralised at the workers.

Furthermore, this chapter shows experiments on validating the behaviour of the tasks during the run-time when some nodes are highly loaded. In these experiments, the current load of the nodes influences the behaviour of the tasks where the HWFarm scheduler lightens the loaded nodes when they become loaded. Also, the

mobility performance is also validated where the compensations are ranging from 12.41% to 57.52% for regular computations and from 23.91% to 59.09% for irregular computations. We observe that even if the accuracy of the estimates in the irregular computations is less accurate, the mobility decisions improve the performance.

This chapter also provides an overhead analysis for all activities of the scheduler, in the master and workers. We study the overhead of the allocation operations, load information operations, and mobility operations. Mobility operations are expected to be the major source of overhead but our experiments suggest that, with the worst movement scenario, the overhead is low compared to the total execution times. As a conclusion, the overhead of the HWFarm skeleton is not exceeding 0.58% compared to the total execution time.

Chapter 6 presents a tool that is able to generate dynamic, precise, adaptive pattern of load across multiple processors. This tool is implemented in C with the MPI and PThread libraries. This tool is effective in dedicated systems for simulating patterns of load changes. This chapter shows how this tool can be used to help evaluating experiments that depend on changing the load on multi-processor platforms.

Chapter 7 evaluates the HWFarm skeleton in terms of its usability, scalability and adaptivity. In this thesis, we propose the HWFarm skeleton as a generic data-parallel framework to run problems in parallel. In this chapter, we demonstrate how this skeleton can run different types of problems as well as its ability to execute algorithms implemented in the pipeline style. Moreover, large scale applications can also be executed by the HWFarm skeleton. Furthermore, this chapter explores the side effects of the adaptivity of the HWFarm skeleton. This adaptivity has three side effects:

- It can produce a global load balancing where the workers try to lighten the loaded nodes by moving tasks from the highly loaded nodes to the lightly loaded nodes. This side effect is shown in the behaviour of the moved tasks in Sec 5.4.1.

- For other applications running along with the skeleton, our experiments show

how the skeleton reduces resource contention in the loaded node and therefore this enables other applications to acquire more processing power. In these experiments, our skeleton adaptivity compensates for the loaded condition where the compensation may reach to 92% for the other applications.

- In terms of the system, our experiments suggest that the adaptivity of our skeleton may improve the throughput of the system.

8.2 Limitations

This section discusses the limitations of HWFarm.

8.2.1 MPI Compatible Platforms

The HWFarm skeleton works on platforms compatible with MPI. We used MPI to facilitate mobility where all created processes have the program code. Furthermore, this simplifies the implementation of the mobility operations between two nodes.

8.2.2 Program Pattern

The program pattern supported by the HWFarm skeleton is loop parallelism. This pattern helps in estimating the remaining iterations when assuming that all iterations have similar execution time. This is somehow true when executing the computation on the same platform with the same load state.

8.2.3 Granularity

The most effective way to exploit HWFarm is solving problems with coarse grain granularity. This is because moving small computations that take few seconds of execution is not efficient. Examples of these problems are: computational intensive algorithms and big data analysis.

8.2.4 GPU Architectures

GPU architectures provide high efficient computational resources but in this work we did not address these architectures for two reasons: the complexity of the implementation; and the overhead of check-pointing and migrating data processed on these architectures.

8.3 Future Work

8.3.1 Data Locality and Mobility

Accessing data efficiently is becoming a big challenge in managing the resources in the parallel systems. In HWFarm, we assumed that the data is included in the task and the task function will be executed over the local data. In some problems, the data is too big and it is difficult to be mobilized amongst the nodes such as analysing a huge database or extracting features from thousands of images. Mapping tasks into computation resources over nodes is maintained by the HWFarm skeleton while accessing the data is moved to the user's responsibility. Then, the user has to manage dealing with data. This issue can be solved when using distributed file system where all nodes in the cluster can access the data transparently. But, other issues regarding the replication and the location of the data will arise. Examples of distributed file system are: HDFS (Hadoop Distributed File System) [124] and GFS (Google File System) [108]. A significant future work can be developed through providing awareness of the location of the replica that is executed by the current process. This can be done by cooperation with the distributed data store or the distributed file system to decide where to run the processes on the nodes where the data is located. Then, in case of mobility, this will be considered to move only to nodes that have the same replicas. Examples of frameworks that take into consideration the replicas when allocating computations are Hadoop [228] and Apache Spark [137].

8.3.2 Fault Tolerance

In distributed systems, a partial failure might occur when a single machine fails while other parts operate correctly. Fault tolerance enables the system to recover from a failure. This is important future work for our HWFarm skeleton. The Master/Worker model implemented in HWFarm helps to perform fault tolerance. This can be done at the master that carries out health check operations to make sure that all workers are running properly. If one worker fails, the master that keeps a track of the running tasks assigns the tasks to other workers.

8.3.3 Memory and Cache

The cost model considers many parameters to be sensitive to the load state of the hosting nodes. The memory and the cache of the host nodes are also important metrics that can be considered to decide that the memory of the executing node is not enough to process the task. In future work, these metrics can be addressed and reflect the actual load state of the executing nodes.

8.3.4 New Skeletons

HWFarm offers a data-parallel skeleton on shared computing platforms with a mobility feature. An important future work can be done to support other types of skeletons: task-parallel and resolution skeletons. We showed how the HWFarm skeleton can perform pipeline programming style but it is more efficient to embed all low level coordination in a separate implementation. Also, a divide and conquer skeleton is another future implementation. There are some problems that require sharing the data in the middle of the execution. Providing a skeleton that addresses this issue is also interesting future work.

8.3.5 Dynamic Allocation Model

In this work, we proposed a static allocation model that decides the number of allocated tasks based on the number of cores. A future work can be developed

through making this model dynamic by taking into consideration the current load of the nodes. Then, based on the load and the number of cores, the allocated tasks for each worker can be identified.

Appendix A

Applications Source Code

This appendix presents the full C code of all applications mentioned in the thesis. Each application calls the skeleton functions and uses the structures defined in Section 3.2.4 to access the data in the worker nodes. The full source code can be found in the link: *https://github.com/talsalkini/hwfarm*.

A.1 Square Numbers Application

```
1  #include <stdio.h>
2  #include <stdlib.h>
3  #include "hwfarm.h"
4
5  void hwfarm_square(hwfarm_task_data* t_data, chFM checkForMobility){
6      int *i = t_data->counter;
7      int *i_max = t_data->counter_max;
8      int *input_p = (int*)t_data->input_data;
9      int *output_p = (int*)t_data->output_data;
10     while(*i < *i_max){
11       *(output_p + (*i)) = (*(input_p + (*i))) * (*(input_p + (*i)));
12       (*i)++;
13       checkForMobility();
14     }
15 }
16
17 int main(int argc, char** argv){
18     initHWFarm(argc,argv);
19     int problem_size = atoi(argv[1]);
20     int chunk = atoi(argv[2]);        // number of items in one task
21     int tasks = problem_size / chunk;  //number of tasks
22     int mobility = atoi(argv[3]);
23     //local input data details
24     int * input_data = NULL;
25     int input_data_size = sizeof(int);
26     int input_data_len = chunk;
27     //output data details
28     int * output_data = NULL;
29     int output_data_size = sizeof(int);
```

```
30      int output_data_len = chunk;
31      //details of the main counter
32      hwfarm_state main_state;
33      main_state.counter = 0;
34      main_state.max_counter = chunk;
35      main_state.state_data = NULL;
36      main_state.state_len = 0;
37      if(rank == 0){
38          //Prepare the input data
39          input_data = (int*)malloc(sizeof(int)*(problem_size));
40          int j=0,k=0;
41          for (j = 0; j < len; j++)
42          input_data[k++] = j+1;
43          //Prepare the output buffer
44          output_data = (int*)malloc(sizeof(int)*(len));
45      }
46
47      hwfarm( hwfarm_square, tasks,
48           input_data, input_data_size, input_data_len,
49           NULL, 0, 0,
50           output_data, output_data_size, output_data_len,
51           main_state, mobility);
52
53      if(rank == 0){
54          //Do something with the output
55          int i=0;
56          for(i=0;i<problem_size;i++)
57              printf("%d\n", *((int*)output_data + (i)));
58      }
59      finalizeHWFarm();
60  }
```

Listing A.1: The Square Numbers application C source code

A.2 Matrix Multiplication Application

```
1   #include <stdio.h>
2   #include <stdlib.h>
3   #include "hwfarm.h"
4
5   void hwfarm_mm(hwfarm_task_data* t_data, chFM checkForMobility){
6       void * mat_a = t_data->input_data;
7       void * mat_b = t_data->shared_data;
8       void * result = t_data->output_data;
9       int *i = (t_data->counter);
10      int *i_max = (t_data->counter_max);
11      int *rows_a = ((int*)t_data->state_data);
12      int *cols_b = ((int*)t_data->state_data)+1;
13      int *mat_s = ((int*)t_data->state_data)+2;
14      int *j = 0;
15      int *k = 0;
16      int *c = 0;
17
18      while((*i) < (*i_max)){
19          while((*j) < (*cols_b)){
20              *(((double*)result) + *c) = 0;
21              double mat_res = 0;
22              while((*k) < (*mat_s)){
```

```
23                  int shift_a = ((*i) * (*mat_s));
24                  int shift_b = ((*j) * (*mat_s));
25                  shift_a = shift_a + *k;
26                  shift_b = shift_b + *k;
27                  double mat_a_item = *(((double*)mat_a) + shift_a);
28                  double mat_b_item = *(((double*)mat_b) + shift_b);
29                  mat_res = mat_res +  (mat_a_item * mat_b_item);
30                  (*k)++;
31              }
32              *(((double*)result) + *c) = mat_res;
33              (*c)++;
34              (*j)++;
35              (*k) = 0;
36          }
37          (*i)++;
38          (*j) = 0;
39          (*k) = 0;
40          checkForMobility();
41      }
42  }
43
44  int main(int argc, char** argv){
45      initHWFarm(argc,argv);
46      int mat_size = atoi(argv[1]);
47      int chunk = atoi(argv[2]);          // number of items in one task
48      int tasks = problem_size / chunk;  //number of tasks
49      int mobility = atoi(argv[3]);
50
51      //local input data details
52      double * input_data = NULL;
53      int input_data_size = sizeof(double);
54      //Total number of items in one task=chunk(number of rows)* matrix size
55      int input_data_len = chunk * mat_size;
56      //shared data details
57      double * shared_data = NULL;
58      int shared_data_size = sizeof(double);
59      int shared_data_len = mat_size * mat_size;
60
61      //output data details
62      double * output_data = NULL;
63      int output_data_size = sizeof(double);
64      //Total number of items in one task = chunk ( number of rows * matrix size)
65      int output_data_len = chunk * mat_size;
66      //details of the main counter
67      hwfarm_state main_state;
68      main_state.counter = 0;
69      main_state.max_counter = chunk;
70      main_state.state_data = NULL;
71      main_state.state_len = 0;
72
73      if(rank == 0){
74          int k = 0, i=0, j=0;
75          //Prepare the input data
76          input_data = (double*)malloc(sizeof(double)*(mat_size*mat_size));
77
78          //initialise the input array with random values
79          for (i = 0; i < mat_size; i++)
80              for (j = 0; j < mat_size; j++)
81                  input_data[k++] = i + j + 1;
82
83          //initialise the shared array with random values
84          shared_data = (double*)malloc(sizeof(double)*(mat_size*mat_size));
85          for (i = 0; i < mat_size; i++)
```

```
86              for (j = 0; j < mat_size; j++)
87                  input_data[k++] = i + j + 2;
88
89          //Prepare the output buffer
90          output_data = (double*)malloc(sizeof(double)*(mat_size*mat_size));
91
92          //State
93          main_state.state_data = (int*)malloc(sizeof(double)*(3));
94          // number of rows in one chunk
95          main_state.state_data[0] = chunk;
96          // number of columns in one chunk
97          main_state.state_data[1] = mat_size;
98          // the size of the matrix
99          main_state.state_data[2] = mat_size;
100         main_state.state_len = 3 * sizeof(int);
101     }
102
103     hwfarm( hwfarm_mm, tasks,
104         input_data, taskDataSize, inputDataSize,
105         shared_data, shared_data_size, shared_data_len,
106         output_data, resultDataSize, outputDataSize,
107         main_state, mobility);
108
109     if(rank == 0){
110         //Do something with the output
111         printToFile(output_data, mat_size);
112     }
113     finalizeHWFarm();
114 }
```

Listing A.2: The Matrix Multiplication application C source code

A.3 Raytracer Application

```
1  #include <stdio.h>
2  #include <stdlib.h>
3  #include <math.h>
4  #include "hwfarm.h"
5
6  struct Poly * Scene;
7
8  struct Coord {
9     double x,y,z;
10    struct Coord * next;
11 };
12
13 struct Vect {
14    double A,B,C;
15    struct Vect * next;
16 };
17
18 struct Ray {
19    struct Coord * c;
20    struct Vect * v;
21    struct Ray * next;
22 };
23
24 struct Poly {
```

```
25    int i;
26    struct Vect * N;
27    struct Coord * Vs;
28    struct Poly * next;
29 };
30
31 struct Impact {
32    double r;
33    int i;
34 };
35
36 struct Impacts{
37    struct Impact * head;
38    struct Impacts * tail;
39 };
40
41 struct MappedRays {
42   double cx,cy,cz,va,vb,vc;
43 };
44
45 struct MappedImpacts {
46   double r;
47   int i;
48 };
49
50 struct iprvals {
51    int xbig,xsmall,ybig,ysmall,zbig,zsmall;
52 };
53
54 struct ripval {
55    int b;
56    int s;
57 };
58
59 void printcoord(struct Coord * c){
60    printf("Coord %lf %lf %lf\n",c->x,c->y,c->z);
61 }
62
63 void printcoords(struct Coord * c){
64    printf("Coords\n");
65    while(c!=NULL){
66       printcoord(c);
67       c=c->next;
68    }
69 }
70
71 void printvect(struct Vect * v){
72    printf("Vect %lf %lf %lf\n",v->A,v->B,v->C);
73 }
74
75 void printvects(struct Vect * v){
76    printf("Vects\n");
77    while(v!=NULL){
78       printvect(v);
79       v=v->next;
80    }
81 }
82
83 void printray(struct Ray * r){
84    printf("Ray\n");
85    printcoords(r->c);
86    printvects(r->v);
87 }
```

```
88
89  void printrays(struct Ray * r){
90      int i=0;
91      while(r!=NULL){
92          printf("i:%d - ",i++);
93          printray(r);
94          r=r->next;
95      }
96  }
97
98  void printpoly(struct Poly * p){
99      printf("Poly %d\n",p->i);
100     printcoords(p->Vs);
101     printvects(p->N);
102 }
103
104 void printpolys(struct Poly * p){
105     printf("Polys\n");
106     while(p!=NULL){
107         printpoly(p);
108         p=p->next;
109     }
110 }
111
112 void printimpact(struct Impact * i){
113     if(i==NULL)
114         printf("No impact\n");
115     else
116         printf("Impact %lf %d\n",i->r,i->i);
117 }
118
119 void printimpacts(struct Impacts * i){
120     printf("Impacts\n");
121     while(i!=NULL){
122         printimpact(i->head);
123         i=i->tail;
124     }
125 }
126
127 void printripval(struct ripval * r){
128     printf("%d %d\n",r->b,r->s);
129 }
130
131 struct MappedRays * mapRays(struct Ray * rays, int raysCount){
132     struct MappedRays * m_rays = (struct MappedRays *)malloc(raysCount * sizeof(struct MappedRays
        ));
133     int i=0;
134     struct Ray * r = rays;
135     while(r != NULL && i < raysCount){
136         m_rays[i].cx = r->c->x;
137         m_rays[i].cy = r->c->y;
138         m_rays[i].cz = r->c->z;
139         m_rays[i].va = r->v->A;
140         m_rays[i].vb = r->v->B;
141         m_rays[i].vc = r->v->C;
142         r=r->next;
143         i++;
144     }
145     return m_rays;
146 }
147
148 void mapImpactsItem(struct MappedImpacts * m_imps, struct Impacts * imp, int impsIndex){
149     if(imp->head != NULL){
```

```
150         m_imps[impsIndex].r = imp->head->r;
151         m_imps[impsIndex].i = imp->head->i;
152     }else{
153         m_imps[impsIndex].r = -1;
154         m_imps[impsIndex].i = -1;
155     }
156 }
157
158 void mapImpacts(struct MappedImpacts * m_imps, struct Impacts * imps, int impsCount){
159     int j=0;
160     struct Impacts * imp = imps;
161     while(imp != NULL && j < impsCount){
162         mapImpactsItem(m_imps, imp, j);
163         imp = imp->tail;
164         j++;
165     }
166 }
167
168 struct Ray * unmapRays(struct MappedRays * m_rays, int raysCount){
169     int i=0;
170     struct Ray * rays = NULL;
171     struct Ray * r = rays;
172     while(i < raysCount){
173         if(r != NULL){
174             r->next = (struct Ray *)malloc(sizeof(struct Ray));
175             r = r->next;
176         }else{
177             rays = (struct Ray *)malloc(sizeof(struct Ray));
178             r = rays;
179         }
180
181         r->c = (struct Coord *)malloc(sizeof(struct Coord));
182         r->c->x = m_rays[i].cx;
183         r->c->y = m_rays[i].cy;
184         r->c->z = m_rays[i].cz;
185         r->c->next = NULL;
186         r->v = (struct Vect *)malloc(sizeof(struct Vect));
187         r->v->A = m_rays[i].va;
188         r->v->B = m_rays[i].vb;
189         r->v->C = m_rays[i].vc;
190         r->v->next = NULL;
191         r->next = NULL;
192         i++;
193     }
194     return rays;
195 }
196
197
198 struct Impacts * unmapImpacts(struct MappedImpacts * m_imps, int impsCount){
199     int j=0;
200     struct Impacts * imps = NULL;
201     struct Impacts * imp = imps;
202     while(j < impsCount){
203         if(imps != NULL){
204             imp->tail = (struct Impacts *)malloc(sizeof(struct Impacts));
205             imp = imp->tail;
206         }else{
207             imps = (struct Impacts *)malloc(sizeof(struct Impacts));
208             imp = imps;
209         }
210         if(m_imps[j].r != -1 && m_imps[j].i != -1){
211             imp->head = (struct Impact *)malloc(sizeof(struct Impact));
212             imp->head->r = m_imps[j].r;
```

```
213             imp->head->i = m_imps[j].i;
214         }else
215             imp->head = NULL;
216 
217             imp->tail = NULL;
218             j++;
219     }
220     return imps;
221 }
222 
223 void printMappedRays(struct MappedRays * m_rays, int raysCount){
224     int i=0;
225     while(i < raysCount){
226         printf("Ray %d:\n", (i+1));
227         printf("CX: %f, CY: %f. CZ: %f, VA: %f, VB: %f, VC: %f\n",
228             m_rays[i].cx, m_rays[i].cy, m_rays[i].cz, m_rays[i].va, m_rays[i].vb, m_rays[i].vc);
229         i++;
230     }
231 }
232 
233 struct Coord * copyCoords(struct Coord * c){
234     if(c == NULL)
235         return NULL;
236     struct Coord * new_c = NULL;
237     struct Coord * new_c_h = new_c;
238     while(c != NULL){
239         if(new_c == NULL){
240             new_c = (struct Coord *) malloc(sizeof(struct Coord));
241             new_c_h = new_c;
242         }else{
243             new_c_h->next = (struct Coord *) malloc(sizeof(struct Coord));
244             new_c_h = new_c_h->next;
245         }
246         new_c_h->x = c->x;
247         new_c_h->y = c->y;
248         new_c_h->z = c->z;
249         new_c_h->next = NULL;
250         c=c->next;
251     }
252     return new_c;
253 }
254 
255 struct Vect * copyVects(struct Vect * v){
256     if(v == NULL)
257         return NULL;
258     struct Vect * new_v = NULL;
259     struct Vect * new_v_h = new_v;
260     while(v != NULL){
261         if(new_v == NULL){
262             new_v = (struct Vect *) malloc(sizeof(struct Vect));
263             new_v_h = new_v;
264         }else{
265             new_v_h->next = (struct Vect *) malloc(sizeof(struct Vect));
266             new_v_h = new_v_h->next;
267         }
268         new_v_h->A = v->A;
269         new_v_h->B = v->B;
270         new_v_h->C = v->C;
271         new_v_h->next = NULL;
272         v=v->next;
273     }
274     return new_v;
275 }
```

```
276
277 struct Poly * copyPolys(struct Poly * p){
278    if(p == NULL)
279       return NULL;
280    struct Poly * new_p = NULL;
281    struct Poly * new_p_h = NULL;
282
283    while(p != NULL){
284       if(new_p == NULL){
285          new_p = (struct Poly *) malloc(sizeof(struct Poly));
286          new_p_h = new_p;
287       }else{
288          new_p_h->next = (struct Poly *) malloc(sizeof(struct Poly));
289          new_p_h = new_p_h->next;
290       }
291       new_p_h->i = p->i;
292       new_p_h->Vs = copyCoords(p->Vs);
293       new_p_h->N = copyVects(p->N);
294       p=p->next;
295    }
296    return new_p;
297 }
298
299 void printiprvals(struct iprvals * i){
300    printf("%d %d %d %d %d %d\n",i->xbig,i->xsmall,i->ybig,
301                                    i->ysmall,i->zbig,i->zsmall);
302 }
303
304 struct iprvals * in_poly_range(double p, double q,
305                                double r, struct Coord *Vs){
306    struct iprvals * results;
307    results=(struct iprvals *)malloc(sizeof(struct iprvals));
308    results->xbig=1;
309    results->xsmall=1;
310    results->ybig=1;
311    results->ysmall=1;
312    results->zbig=1;
313    results->zsmall=1;
314    while(Vs!=NULL){
315       results->xbig=results->xbig && p>Vs->x+1E-8;
316       results->xsmall=results->xsmall && p<Vs->x-1E-8;
317       results->ybig=results->ybig && q>Vs->y+1E-8;
318       results->ysmall=results->ysmall && q<Vs->y-1E-8;
319       results->zbig=results->zbig && r>Vs->z+1E-8;
320       results->zsmall=results->zsmall && r<Vs->z-1E-8;
321       Vs=Vs->next;
322    }
323    return results;
324 }
325
326 int cross_dot_sign (double a, double b, double c, double d, double e,
327                     double f, double A, double B, double C){
328    double P,Q,R,cd;
329    P=b*f-e*c;
330    Q=d*c-a*f;
331    R=a*e-d*b;
332    cd=P*A+Q*B+R*C;
333    if(cd<0.0)
334       return -1;
335    else
336       return 1;
337 }
338
```

```
339 struct ripval * really_in_poly(double p, double q, double r, double A,
340                                 double B, double C, struct Coord * Vs){
341    struct ripval * results;
342    int s1;
343    if(Vs->next->next==NULL){
344       results=(struct ripval *)malloc(sizeof(struct ripval));
345       results->b=1;
346       results->s=cross_dot_sign (Vs->next->x-p,Vs->next->y-q,Vs->next->z-r,
347                                  Vs->next->x-Vs->x,Vs->next->y-Vs->y,
348                                  Vs->next->z-Vs->z,A,B,C);
349       return results;
350    }
351    results=really_in_poly(p,q,r,A,B,C,Vs->next);
352    if(results->b){
353       s1=cross_dot_sign (Vs->next->x-p,Vs->next->y-q,Vs->next->z-r,
354                          Vs->next->x-Vs->x,Vs->next->y-Vs->y,
355                          Vs->next->z-Vs->z,A,B,C);
356       if(s1==results->s){
357          results->b=1;
358          results->s=s1;
359       }else{
360          results->b=0;
361          results->s=0;
362       }
363    }
364    return results;
365 }
366
367 int in_poly_test(double p, double q, double r, double A,
368                  double B, double C, struct Coord * Vs){
369    struct iprvals * iprcheck;
370    struct ripval * ripcheck;
371    iprcheck = in_poly_range (p,q,r,Vs);
372    if(iprcheck->xbig || iprcheck->xsmall ||
373     iprcheck->ybig || iprcheck->ysmall ||
374     iprcheck->zbig || iprcheck->zsmall){
375       free(iprcheck);
376       return 0;
377    }
378    ripcheck=really_in_poly(p,q,r,A,B,C,Vs);
379    int b = ripcheck->b;
380    free(ripcheck);
381    return b;
382 }
383
384 void TestForImpact(struct Ray * ray, struct Poly * poly, struct Impact * imp){
385    double px,py,pz;
386    double u,v,w,l,m,n;
387    double distance;
388    double p,q,r;
389    u=ray->c->x;
390    v=ray->c->y;
391    w=ray->c->z;
392    l=ray->v->A;
393    m=ray->v->B;
394    n=ray->v->C;
395    px=poly->Vs->x;
396    py=poly->Vs->y;
397    pz=poly->Vs->z;
398    distance=(poly->N->A*(px-u)+poly->N->B*(py-v)+poly->N->C*(pz-w))/
399             (poly->N->A*l+poly->N->B*m+poly->N->C*n);
400    p=u+distance*l;
401    q=v+distance*m;
```

```
402     r=w+distance*n;
403     if(!in_poly_test(p,q,r,poly->N->A,poly->N->B,poly->N->C,poly->Vs)){
404         imp->r = -1;
405         imp->i = -1;
406     }else{
407         imp->r=distance;
408         imp->i=poly->i;
409     }
410 }
411
412 void earlier(struct Impact *currentImpact, struct Impact * newImpact){
413     if(currentImpact->r != -1 && newImpact->r != -1){
414         if(currentImpact->r > newImpact->r){
415             currentImpact->r = newImpact->r;
416             currentImpact->i = newImpact->i;
417         }
418     }
419     if(currentImpact->r == -1 && newImpact->r != -1){
420         currentImpact->r = newImpact->r;
421         currentImpact->i = newImpact->i;
422     }
423 }
424
425 struct Impact * insert(struct Impacts * i){
426     struct Impact * e = NULL;
427     while(i != NULL){
428         earlier(i->head,e);
429         i = i->tail;
430     }
431     if(  e == NULL)
432         return NULL;
433     else{
434         struct Impact * ie;
435         ie=(struct Impact *)malloc(sizeof(struct Impact));
436         ie->r=e->r;
437         ie->i=e->i;
438         return ie;
439     }
440 }
441
442 struct Impact * FirstImpact(struct Poly * os, struct Ray * r){
443     if(os==NULL)
444         return NULL;
445     struct Poly * o = os;
446     struct Impact* currentImpact = (struct Impact *)malloc(sizeof(struct Impact));
447     struct Impact* newImpact = (struct Impact *)malloc(sizeof(struct Impact));
448     TestForImpact( r, o, currentImpact);
449     o = o->next;
450
451     while(o != NULL){
452         TestForImpact( r, o, newImpact);
453         earlier(currentImpact, newImpact);
454         o = o->next;
455     }
456     return currentImpact;
457 }
458
459 double root(double x, double r){
460     if(x<0.00000001 && -0.00000001<x)
461         return 0.0;
462     while(fabs((r*r-x)/x)>=0.0000001)
463         r=(r+x/r)/2.0;
464     return r;
```

```
465 }
466
467 struct Vect * VAdd(struct Vect * v1,struct Vect * v2){
468    struct Vect * v;
469    v=(struct Vect *)malloc(sizeof(struct Vect));
470    v->A=v1->A+v2->A;
471    v->B=v1->B+v2->B;
472    v->C=v1->C+v2->C;
473    return v;
474 }
475
476 struct Vect * VMult(double n, struct Vect * v1){
477    struct Vect * v;
478    v=(struct Vect *)malloc(sizeof(struct Vect));
479    v->A=n*v1->A;
480    v->B=n*v1->B;
481    v->C=n*v1->C;
482    return v;
483 }
484
485 struct Vect * ray_points( int i, int j, int Detail, struct Vect * v,
486                           struct Vect * Vx, struct Vect * Vy){
487    struct Vect * iVx,* jVy,* newv;
488    if(j==Detail)
489       return NULL;
490    if(i==Detail)
491       return ray_points(0,j+1,Detail,v,Vx,Vy);
492    iVx=VMult(((double)i)/((double)(Detail-1)),Vx);
493    jVy=VMult(((double)j)/((double)(Detail-1)),Vy);
494    newv=VAdd(VAdd(v,iVx),jVy);
495    newv->next=ray_points(i+1,j,Detail,v,Vx,Vy);
496    return newv;
497 }
498
499 struct Ray * GenerateRays(int Det, double X, double Y, double Z){
500    double d;
501    double Vza,Vzb,Vzc;
502    double ab;
503    double ya,yb,yc;
504    double ysize;
505    struct Vect * v;
506    struct Vect * rps,* VX,* VY;
507    struct Ray * newrays,* t;
508    d=root(X*X+Y*Y+Z*Z,1.0);
509    Vza=(-4.0*X/d);Vzb=(-4.0*Y/d);Vzc=(-4.0*Z/d);
510    ab=root(Vza*Vza+Vzb*Vzb,1.0);
511    VX=(struct Vect *)malloc(sizeof(struct Vect));
512    VX->A=Vzb/ab;VX->B=(-Vza/ab);VX->C=0.0;
513    ya=Vzb*VX->C-VX->B*Vzc;
514    yb=VX->A*Vzc-Vza*VX->C;
515    yc=Vza*VX->B-VX->A*Vzb;
516    ysize=root(ya*ya+yb*yb+yc*yc,1.0);
517    VY=(struct Vect *)malloc(sizeof(struct Vect));
518    VY->A=ya/ysize;VY->B=yb/ysize;VY->C=yc/ysize;
519    if(VY->C>0.0){
520       VX->A=(-VX->A);VX->B=(-VX->B);VX->C=(-VX->C);
521       VY->A=(-VY->A);VY->B=(-VY->B);VY->C=(-VY->C);
522    }
523
524    v=(struct Vect *)malloc(sizeof(struct Vect));
525    v->A=X+Vza-(VX->A+VY->A)/2.0;
526    v->B=Y+Vzb-(VX->B+VY->B)/2.0;
527    v->C=Z+Vzc-(VX->C+VY->C)/2.0;
```

```
528     rps=ray_points(0,0,Det,v,VX,VY);
529
530     if(rps==NULL)
531         return NULL;
532     newrays=(struct Ray *)malloc(sizeof(struct Ray));
533     newrays->c=(struct Coord *)malloc(sizeof(struct Coord));
534     newrays->c->x=X;
535     newrays->c->y=Y;
536     newrays->c->z=Z;
537     newrays->v=(struct Vect *)malloc(sizeof(struct Vect));
538     newrays->v->A=rps->A-X;
539     newrays->v->B=rps->B-Y;
540     newrays->v->C=rps->C-Z;
541     t=newrays;
542     rps=rps->next;
543
544     while(rps!=NULL){
545         t->next=(struct Ray *)malloc(sizeof(struct Ray));
546         t=t->next;
547         t->c=(struct Coord *)malloc(sizeof(struct Coord));
548         t->c->x=X;
549         t->c->y=Y;
550         t->c->z=Z;
551         t->v=(struct Vect *)malloc(sizeof(struct Vect));
552         t->v->A=rps->A-X;
553         t->v->B=rps->B-Y;
554         t->v->C=rps->C-Z;
555         rps=rps->next;
556     }
557     t->next=NULL;
558     return newrays;
559 }
560
561 void showimps(int dv, int i, struct Impacts * imps){
562     FILE *fres = fopen("finalResult.txt","w");
563     while(imps != NULL){
564         if(i==0){
565             fprintf(fres,"\n");
566             i=dv;
567         }
568         if(imps->head == NULL){
569             fprintf(fres,"%2c",'.');
570         }else{
571             fprintf(fres,"%2d",imps->head->i);
572         }
573         fprintf(fres," ");
574         i=i-1;
575         imps=imps->tail;
576     }
577     fprintf(fres,"\n");
578     fclose(fres);
579 }
580
581 struct Poly * getPoly(FILE * scene_file, int id){
582     struct Poly * p;
583     struct Coord * t;
584     p=(struct Poly *) malloc(sizeof(struct Poly));
585     p->i=id;
586     p->N=(struct Vect *)malloc(sizeof(struct Vect));
587     int numOfI = -1;
588     numOfI = fscanf(scene_file,"%lf %lf %lf",&(p->N->A),&(p->N->B),&(p->N->C));
589     numOfI = fscanf(scene_file,"%d",&id);
590     p->Vs=(struct Coord *)malloc(sizeof(struct Coord));
```

```
591     t=p->Vs;
592     numOfI = fscanf(scene_file,"%lf %lf %lf",&(t->x),&(t->y),&(t->z));
593     t=p->Vs;
594     while(--id){
595        t->next=(struct Coord *)malloc(sizeof(struct Coord));
596        t=t->next;
597        numOfI = fscanf(scene_file,"%lf %lf %lf",&(t->x),&(t->y),&(t->z));
598     }
599     t->next=NULL;
600     return p;
601  }
602
603  struct Poly * getScene(char * scene_file_name, int limit){
604     FILE * scene_file = fopen(scene_file_name,"r");
605     if(scene_file == NULL){
606        printf("can't open %s\n",scene_file_name);
607        exit(0);
608     }
609
610     struct Poly * s,* t;
611     int id;
612     if(fscanf(scene_file,"%d",&id) == EOF){
613        fclose(scene_file);
614        return NULL;
615     }
616     s = getPoly(scene_file,id);
617     t=s;
618     int i=0;
619     while(fscanf(scene_file,"%d",&id) != EOF){
620        if(limit <= i++)
621           break;
622        t->next = getPoly(scene_file,id);
623        t = t->next;
624     }
625     t->next = NULL;
626     fclose(scene_file);
627     return s;
628  }
629
630  void hwfarm_rt( hwfarm_task_data* t_data, chFM checkForMobility){
631     struct Ray * rays = unmapRays(t_data->input_data, t_data->input_len);
632     if(rays==NULL)
633        return;
634     //Get the counter value
635     int *main_index = (t_data->counter);
636     //The head of the imapct array
637     struct Impacts * imps = NULL;
638     // An auxiliary pointer
639     struct Impacts * t = imps;
640     int i=0;
641     //Navigate to the unprocessed ray ( to consider the moved tasks)
642     while(rays!=NULL && i < *main_index){
643        rays=rays->next;
644        i++;
645     }
646     while(rays!=NULL){
647        if(imps == NULL){
648           imps = (struct Impacts *)malloc(sizeof(struct Impacts));
649           t = imps;
650        }else{
651           t->tail=(struct Impacts *)malloc(sizeof(struct Impacts));
652           t=t->tail;
653        }
```

```
654         t->head = FirstImpact(Scene, rays);
655         rays=rays->next;
656         mapImpactsItem(t_data->output_data, t, *main_index);
657         *main_index = (*main_index) + 1;
658         checkForMobility();
659       }
660       t->tail=NULL;
661   }
662
663   int main(int argc, char** argv){
664     initHWFarm(argc,argv);
665
666     //Details refers to the number of rays in one dimension
667     int Details = atoi(argv[1]);
668     int chunk = atoi(argv[2]);
669     char* scene_file = (argv[3]);
670     int scene_limit = atoi(argv[4]);
671     int mobility = atoi(argv[5]);
672     int problem_size = Details * Details;
673     int tasks = problem_size / chunk;
674     float ViewX = 10.0;
675     float ViewY = 10.0;
676     float ViewZ = 10.0;
677     //input
678     void * input_data = NULL;
679     int input_data_size = sizeof(struct MappedRays);
680     int input_data_len = chunk;
681     //output
682     void * output_data = NULL;
683     int output_data_size = sizeof(struct MappedImpacts);
684     int output_data_len = chunk;
685     hwfarm_state main_state;
686     main_state.counter = 0;
687     main_state.max_counter = chunk;
688     main_state.state_data = NULL;
689     main_state.state_len = 0;
690     if(rank == 0){
691       //Input data
692       struct Ray * rays;
693       rays=GenerateRays(Details,ViewX,ViewY,ViewZ);
694       struct MappedRays * mapped_rays;
695       mapped_rays = mapRays(rays, Details*Details);
696       input_data = mapped_rays;
697       //Output Data
698       output_data = malloc(output_data_size * problem_size);
699     }else{
700       Scene = getScene(scene_file, scene_limit);
701     }
702
703     hwfarm( hwfarm_rt, tasks,
704           input_data, input_data_size, input_data_len,
705           NULL, 0, 0,
706           output_data, output_data_size, output_data_len,
707           main_state, mobility);
708
709     if(rank == 0){
710       struct Impacts * new_imps = unmapImpacts(output_data, problem_size);
711       //Print impact to a file
712       showimps(Details, Details, new_imps);
713     }
714
715     finalizeHWFarm();
716     return 1;
```

```
717 }
```

Listing A.3: The Raytracer application C source code

A.4 Molecular Dynamics Application

```
1  #include <stdio.h>
2  #include <stdlib.h>
3  #include <math.h>
4  #include "hwfarm.h"
5
6  #define N 100000
7  #define G 6.673e-11
8  #define TIMESTAMP 1e11
9
10 struct Particle{
11    double rx, ry; //position components
12    double vx, vy; //velocity components
13    double fx, fy; //force components
14    double mass;   //mass of the particle
15 };
16
17 struct Particle Update(struct Particle p, double timestamp){
18    p.vx += timestamp*p.fx / p.mass;
19    p.vy += timestamp*p.fy / p.mass;
20    p.rx += timestamp*p.vx;
21    p.ry += timestamp*p.vy;
22    return p;
23 }
24
25 void PrintParticle(struct Particle p){
26    printf("[%d]. %f\n%f\n%f\n%f\n%f\n%f\n%f\n\n", rank, p.rx,p.ry,p.vx,p.vy,p.fx, p.fy, p.mass);
27 }
28
29 struct Particle CopyParticle(struct Particle p_to, struct Particle p_from){
30    p_to.fx = p_from.fx;
31    p_to.fy = p_from.fy;
32    p_to.rx = p_from.rx;
33    p_to.ry = p_from.ry;
34    p_to.vx = p_from.vx;
35    p_to.vy = p_from.vy;
36    p_to.mass = p_from.mass;
37    return p_to;
38 }
39
40 //Reset the forces on particle
41 struct Particle ResetForce(struct Particle p){
42    p.fx = 0.0;
43    p.fy = 0.0;
44    return p;
45 }
46
47 //Add force to particle a by particle b
48 struct Particle AddForce(struct Particle a,struct Particle b){
49    //To avoid infinities
50    double EPS = 3E4;
51    double dx = b.rx - a.rx;
52    double dy = b.ry - a.ry;
```

```
53    double dist = sqrt(dx*dx + dy*dy);
54    double F = (G * a.mass * b.mass) / (dist*dist + EPS*EPS);
55    a.fx += F * dx / dist;
56    a.fy += F * dy / dist;
57    return a;
58 }
59
60 void hwfarm_nbody( hwfarm_task_data* t_data, chFM checkForMobility){
61    int *i = t_data->counter;
62    int *i_max = t_data->counter_max;
63    int shared_len = t_data->shared_len;
64    int cur_i = 0, j = 0;
65    struct Particle *shared_p = (struct Particle *)t_data->shared_data;
66    struct Particle *output_p = (struct Particle *)t_data->output_data;
67    while(*i < *i_max){
68       cur_i = (*i) + (*(t_data->counter_max) * t_data->task_id);
69       output_p[*i] = CopyParticle(output_p[*i], shared_p[cur_i]);
70       output_p[*i] = ResetForce(output_p[*i]);
71       for (j = 0; j < shared_len; j++){
72          if (cur_i != j){
73             output_p[*i] = AddForce(output_p[*i], shared_p[j]);
74          }
75       }
76       output_p[*i] = Update(output_p[*i], TIMESTAMP);
77       (*i)++;
78       checkForMobility();
79    }
80 }
81
82 void readParticles(struct Particle* particles, int n){
83    FILE* f;
84    if((f=fopen("test_data","r")) == NULL){
85       printf("Cannot open file.\n");
86       exit(0);
87    }
88    double d = 0.0;
89
90    int l = 0;
91    int i = 0;
92    while(i<n){
93       l = fscanf(f, "%lf\n", &d);
94       particles[i].rx = d;
95       l = fscanf(f, "%lf\n", &d);
96       particles[i].ry = d;
97       l = fscanf(f, "%lf\n", &d);
98       particles[i].vx = d;
99       l = fscanf(f, "%lf\n", &d);
100      particles[i].vy = d;
101      l = fscanf(f, "%lf\n", &d);
102      particles[i].fx = d;
103      l = fscanf(f, "%lf\n", &d);
104      particles[i].fx = d;
105      l = fscanf(f, "%lf\n", &d);
106      particles[i].mass = d;
107      i++;
108   }
109   fclose(f);
110 }
111
112 int main(int argc, char** argv){
113    initHWFarm(argc,argv);
114
115    int problem_size = N;
```

```
116     int chunk = atoi(argv[1]);
117     int tasks = problem_size / chunk;
118     int mobility =  atoi(argv[2]);
119 
120     //input
121     void * input_data = NULL;
122     int input_data_size = 0;
123     int input_data_len = 0;
124 
125     //shared
126     struct Particle * shared_data = NULL;
127     int shared_data_size = sizeof(struct Particle);
128     int shared_data_len = N;
129 
130     //output
131     struct Particle *output_data = NULL;
132     int output_data_size = sizeof(struct Particle);
133     int output_data_len = chunk;
134 
135     hwfarm_state main_state;
136     main_state.counter = 0;
137     main_state.max_counter = chunk;
138     main_state.state_data = NULL;
139     main_state.state_len = 0;
140 
141     if(rank == 0){
142        struct Particle * particles = (struct Particle *)malloc(sizeof(struct Particle)*N);
143 
144        readParticles(particles, N);
145 
146        //Shared data
147        shared_data = particles;
148 
149        //Output Data
150        output_data = malloc(problem_size * output_data_size);
151     }
152 
153     int numberofiterations = 10;
154     int count = 0;
155     while (count < numberofiterations){
156     hwfarm( hwfarm_nbody, tasks,
157           input_data, input_data_size, input_data_len,
158           shared_data, shared_data_size, shared_data_len,
159           output_data, output_data_size, output_data_len,
160           main_state, mobility);
161 
162        if(rank == 0){
163           shared_data = output_data;
164        }
165        count++;
166     }
167     if(rank == 0){
168        //print the output to a file (output_data, problem_size)
169     }
170 
171     finalizeHWFarm();
172 
173     return 1;
174 }
```

Listing A.4: The Molecular Dynamics application C source code

A.5 BLAST Application

```
1  #include <stdio.h>
2  #include <stdlib.h>
3  #include <string.h>
4  #include <math.h>
5  #include "hwfarm.h"
6
7  #define WORD_LEN 3
8
9  struct word{
10    //3 for neclutides
11    char value[WORD_LEN];
12 };
13
14 //find the given pattern in the search string
15 int find(char *search, char *pattern, int slen, int plen) {
16    int i, j, k;
17    int score = 0;
18    int * scores = (int*)malloc(sizeof(int)*(slen - plen + 1));
19    for (i = 0; i <= slen - plen; i++) {
20       score = 0;
21       for (j = 0, k = i; (j < plen); j++, k++){
22          if(search[k] == pattern[j])
23             score += 1;
24          else
25             score += -3;
26       }
27       scores[i] = score;
28       if (j == plen)
29          score = i;
30    }
31
32    int max_score = scores[0];
33    int max_score_location = 0;
34
35    for(i=0;i<slen - plen + 1;i++){
36       if(max_score <= scores[i]){
37          max_score = scores[i];
38          max_score_location = i;
39       }
40    }
41
42    free (scores);
43    return max_score;
44 }
45
46 int readGenes(char *search, int n){
47    FILE* f;
48    if((f=fopen("db/chr.fsa","r")) == NULL){
49       printf("Cannot open file.\n");
50       exit(0);
51    }
52
53    char*tmp = (char*)malloc(100);
54
55    int i = 0, tmp_i = 0, l = 0;
56    l = fscanf(f, "%s\n", tmp);
57    while(l != -1){
58       while(tmp[tmp_i] != '\0' && tmp[tmp_i] != '\n'){
59          search[i] = tmp[tmp_i];
60          tmp_i++; i++;
```

```
61              if(i >= n) break;
62          }
63          if(i >= n) break;
64          tmp_i = 0;
65          l = fscanf(f, "%s\n", tmp);
66      }
67      free (tmp);
68      fclose(f);
69      return i;
70  }
71
72  void printGenes(char *search, int n){
73      int i = 0;
74      while(i < n){
75          printf("i: %d - search: %c\n", i, search[i]);
76          i++;
77      }
78  }
79
80  void printWords(struct word * words, int len){
81      int i=0;
82      for(i=0;i<len;i++){
83          printf("word %d: %s\n", i,words[i].value);
84      }
85  }
86
87  struct word * getSubs(char *pattern, int plen){
88      int words_len = plen - WORD_LEN + 1;
89      struct word * words = (struct word *)malloc(sizeof(struct word)*(words_len));
90      int i = 0;
91      for(i =0;i<words_len;i++){
92          words[i].value[0] = pattern[i];
93          words[i].value[1] = pattern[i+1];
94          words[i].value[2] = pattern[i+2];
95      }
96      return words;
97  }
98
99  void hwfarm_blast( hwfarm_task_data* t_data, chFM checkForMobility){
100     int *i = t_data->counter;
101     int *i_max = t_data->counter_max;
102     int *output_p = (int *)t_data->output_data;
103     struct word * words = t_data->input_data;
104     char * shared_p = (char *)t_data->shared_data;
105     int input_len = t_data->input_len;
106
107     while(*i < *i_max){
108         output_p[*i] = find(shared_p, words[*i].value, input_len, WORD_LEN);
109         (*i)++;
110         checkForMobility();
111     }
112 }
113
114 int main(int argc, char** argv){
115     initHWFarm(argc,argv);
116
117     int problem_size = atoi(argv[1]);
118     int tasks = atoi(argv[2]);
119     int mobility = atoi(argv[3]);
120     //input data
121     void * input_data = NULL;
122     int input_data_size = sizeof(struct word);
123     int input_data_len = 0;
```

```
124     //shared data
125     char * shared_data = NULL;
126     int shared_data_size = sizeof(char);
127     int shared_data_len = problem_size;
128     //output data
129     int *output_data = NULL;
130     int output_data_size = sizeof(int);
131     int output_data_len = 0;
132
133     hwfarm_state main_state;
134     main_state.counter = 0;
135     main_state.max_counter = 0;
136     main_state.state_data = NULL;
137     main_state.state_len = 0;
138
139     if(rank == 0){
140        //input ( the words that would be distrbuted into tasks )
141        char * pattern = "CTGGCCATTACTAGAAGAAGAA";
142        int num_of_sub = strlen(pattern) - WORD_LEN + 1;
143        input_data = getSubs(pattern, strlen(pattern));
144        int chunk = num_of_sub / tasks;
145        input_data_len = chunk;
146
147        //shared data is the sequences of genes
148        char * blast_input_data = (char*)malloc(sizeof(char)*problem_size);
149        readGenes(blast_input_data, problem_size);
150        shared_data = blast_input_data;
151        shared_data_len = problem_size;
152
153        //Output Data(in this example the output is based on the search pattern)
154        output_data = malloc(output_data_size*num_of_sub);
155        output_data_len = chunk;
156
157      //modify state data based on the search pattern
158        main_state.max_counter = chunk;
159     }
160
161     hwfarm( hwfarm_blast, tasks,
162           input_data, input_data_size, input_data_len,
163           shared_data, shared_data_size, shared_data_len,
164           output_data, output_data_size, output_data_len,
165           main_state, mobility);
166
167     if(rank == 0){
168        //print the output to a file (output_data, num_of_sub)
169     }
170
171      finalizeHWFarm();
172
173   return 1;
174 }
```

Listing A.5: The BLAST application C source code

A.6 findWord Application

```
1 #include <stdio.h>
2 #include <stdlib.h>
```

```
3  #include <string.h>
4  #include <sys/stat.h>
5
6  #include "hwfarm.h"
7
8  struct db_file_path{
9     int file_id;
10    char file_path[50];
11    char file_output_path[50];
12 };
13
14 void printPath(struct db_file_path p){
15    printf("[%d]. File info {%d}.....\nPath: %s\nOutput: %s\n\n", rank,
16            p.file_id, p.file_path, p.file_output_path);
17 }
18
19 void printAllPaths(struct db_file_path * ps, int n){
20    int i = 0;
21    for(;i<n;i++)
22       printPath(ps[i]);
23 }
24
25 int readLocalFile(char *file_name){
26    FILE* f;
27    if((f=fopen(file_name,"r")) == NULL){
28       printf("Cannot open file.\n");
29    }
30    char*tmp = (char*)malloc(1000);
31    int i = 0;
32    int l = 0;
33    l = fscanf(f, "%s\n", tmp);
34    while(l != -1){
35       l = fscanf(f, "%s\n", tmp);
36    }
37    free (tmp);
38    fclose(f);
39    return i;
40 }
41
42 void printFile(char *search, int n){
43    int i = 0;
44    while(i < n){
45       printf("i: %d - search: %c\n", i, search[i]);
46       i++;
47    }
48 }
49
50 char SMALL_A = 'a';
51 char SMALL_Z = 'z';
52 char CAP_A = 'A';
53 char CAP_Z = 'Z';
54 int TOTAL_ALPH = 26;
55
56 void setAlph(int * alph, int n, char c){
57    if(c >= SMALL_A && c <= SMALL_Z){
58       c = c - 32 - 65;
59       alph[(int)c]++;
60       return;
61    }
62    if(c >= CAP_A && c <= CAP_Z){
63       c = c - 65;
64       alph[(int)c]++;
65       return;
```

```
66      }
67  }
68
69  void printAlph(int * alph, int n){
70      int i;
71      for(i=0;i<n;i++)
72          printf("[%d]. %c %d\n", rank, (i+65), alph[i]);
73  }
74
75  void printAlphToFile(char * output_path, int * alph, int n){
76      FILE* f_output;
77      if((f_output=fopen(output_path,"w")) == NULL){
78          printf("Cannot open file(%s).\n", output_path);
79      }
80      int i;
81      for(i=0;i<n;i++)
82          fprintf(f_output, "%c %d\n", (i+65), alph[i]);
83      fclose(f_output);
84  }
85
86  void printStatsToFile(char * output_path, char* caption, int value){
87      FILE* f_output;
88      if((f_output=fopen(output_path,"a")) == NULL){
89          printf("Cannot open file(%s).\n", output_path);
90      }
91
92      fprintf(f_output, "\n%s: %d\n", caption, value);
93      fclose(f_output);
94  }
95
96  void resetAlph(int * alph, int n){
97      int i;
98      for(i=0;i<n;i++)
99          alph[i] = 0;
100 }
101
102 int isDot(char * w){
103     int i=0;
104     for(i=0;i<strlen(w);i++){
105         if(w[i]=='.')
106             return 0;
107     }
108     return 1;
109 }
110
111 void countWords(struct db_file_path file_p){
112     FILE* f_input ;
113     if((f_input=fopen(file_p.file_path,"r")) == NULL){
114         printf("Cannot open file(%s).\n", file_p.file_path);
115     }
116     int c = 0;
117     char wordX[1024];
118     while (fscanf(f_input, " %1023s", wordX) == 1) {
119         if(isDot(wordX))
120             c++;
121     }
122     fclose(f_input);
123     printStatsToFile(file_p.file_output_path, "Count Words", c);
124 }
125
126 struct file_word{
127     char value[30];
128     int occurance;
```

```
129 };
130
131 void resetAllWords(struct file_word * all_w, int n){
132    int i;
133    for(i=0;i<n;i++){
134       strcpy(all_w[i].value, "");
135       all_w[i].occurance = 0;
136    }
137 }
138
139 void addWord(struct file_word * all_w, int n, char * word){
140    int i;
141    for(i=0;i<n;i++){
142       if(all_w[i].occurance == 0){
143          strcpy(all_w[i].value, word);
144          all_w[i].occurance = 1;
145          return;
146       }
147       if(strcmp(word, all_w[i].value) == 0){
148          all_w[i].occurance++;
149          return;
150       }
151    }
152 }
153
154 void addWordWithOcc(struct file_word * all_w, int n, char * word, int occ){
155    int i;
156    for(i=0;i<n;i++){
157       if(all_w[i].occurance == 0){
158          strcpy(all_w[i].value, word);
159          all_w[i].occurance = occ;
160          return;
161       }
162       if(strcmp(word, all_w[i].value) == 0){
163          all_w[i].occurance = all_w[i].occurance + occ;
164          return;
165       }
166    }
167 }
168
169 void printAllWords(struct file_word * all_w, int n){
170    int i;
171    for(i=0;i<n;i++){
172       if(all_w[i].occurance == 0){
173          if(i==0) printf("[%d]. No words...\n",rank);
174             return;
175       }
176       printf("[%d]. Word(%d): %-20s with %d occurances..\n", rank, i, all_w[i].value,all_w[i].
      occurance);
177    }
178 }
179
180 void printAllWordsToFile(char * output_path, struct file_word * all_w, int n){
181    FILE* f_output;
182    if((f_output=fopen(output_path,"a")) == NULL){
183       printf("Cannot open file(%s).\n", output_path);
184    }
185
186    fprintf(f_output, "\nList of Words:\n");
187
188    int i;
189    for(i=0;i<n;i++){
190       if(all_w[i].occurance == 0)break;
```

```
191             fprintf(f_output,"%s : %d\n", all_w[i].value,all_w[i].occurance);
192         }
193
194         fclose(f_output);
195     }
196
197     void printStage2WordsToFile(char * output_path, struct file_word * all_w, int n){
198         FILE* f_output;
199         if((f_output=fopen(output_path,"w")) == NULL){
200             printf("Cannot open file(%s).\n", output_path);
201         }
202
203         int i;
204         for(i=0;i<n;i++){
205             if(all_w[i].occurance == 0)break;
206             fprintf(f_output,"%s : %d\n", all_w[i].value,all_w[i].occurance);
207         }
208         fclose(f_output);
209     }
210
211     int validStart(char * w){
212         int c = w[0];
213         if((c <= SMALL_Z && c >= SMALL_A) || (c <= CAP_Z && c >= CAP_A)){
214             return 1;
215         }
216         return 0;
217     }
218
219     int validWord(char * w){
220         int i = 0;
221         int c;
222         if(strlen(w)>25) return 0;
223         for(i=0;i<strlen(w);i++){
224             c = w[i];
225             if(!((c <= SMALL_Z && c >= SMALL_A)
226                 || (c <= CAP_Z && c >= CAP_A)
227                 || (c <= '9' && c >= '0'))){
228                 return 0;
229             }
230         }
231         return 1;
232     }
233
234     void filterWord(char * w){
235         int c = w[strlen(w)-1];
236         if((c == ':')||(c == '!')||(c == ',')||(c == '.')||(c == '?')||(c == ')')||(c == '"')){
237             w[strlen(w)-1] = '\0';
238         }
239     }
240
241     void getWords(struct db_file_path file_p){
242         FILE* f_input ;
243         if((f_input=fopen(file_p.file_path,"r")) == NULL){
244             printf("Cannot open file(%s).\n", file_p.file_path);
245         }
246         char wordX[1024];
247         struct file_word * all_words = (struct file_word *)malloc(sizeof(struct file_word)*1000);
248         resetAllWords(all_words, 1000);
249         while (fscanf(f_input, "%1023s", wordX) == 1) {
250             if(isDot(wordX)){
251                 filterWord(wordX);
252                 if(validStart(wordX) && validWord(wordX))
253                     addWord(all_words, 1000, wordX);
```

```
254         }
255     }
256     fclose(f_input);
257     printAllWordsToFile(file_p.file_output_path, all_words, 1000);
258     free(all_words);
259 }
260 
261 void calcLongestWord(struct db_file_path file_p){
262     FILE* f_input ;
263     if((f_input=fopen(file_p.file_path,"r")) == NULL){
264         printf("Cannot open file(%s).\n", file_p.file_path);
265     }
266     char wordX[1024];
267     int longest = 0;
268     while (fscanf(f_input, "%1023s", wordX) == 1) {
269         if(isDot(wordX)){
270             if(longest < strlen(wordX)){
271                 longest = strlen(wordX);
272             }
273         }
274     }
275     fclose(f_input);
276     printStatsToFile(file_p.file_output_path, "Longest Words length", longest);
277 }
278 
279 void calcAlph(struct db_file_path file_p){
280     FILE* f_input ;
281     if((f_input=fopen(file_p.file_path,"r")) == NULL){
282         printf("Cannot open file(%s).\n", file_p.file_path);
283     }
284     int * alph = (int*)malloc(sizeof(int)*TOTAL_ALPH);
285     int c;
286     resetAlph(alph, TOTAL_ALPH);
287     while((c = fgetc(f_input)) != EOF) {
288         setAlph(alph, TOTAL_ALPH, c);
289     }
290     fclose(f_input);
291     printAlphToFile(file_p.file_output_path, alph, TOTAL_ALPH);
292     free(alph);
293 }
294 
295 void countLetters(struct db_file_path file_p){
296     FILE* f_input ;
297     if((f_input=fopen(file_p.file_path,"r")) == NULL){
298         printf("Cannot open file(%s).\n", file_p.file_path);
299     }
300 
301     int count = 0;
302     int c;
303     while((c = fgetc(f_input)) != EOF) {
304         count++;
305     }
306     fclose(f_input);
307     printStatsToFile(file_p.file_output_path, "Count Letters", count);
308 }
309 
310 void processFile(struct db_file_path file_p){
311     calcAlph(file_p);
312     countWords(file_p);
313     countLetters(file_p);
314     calcLongestWord(file_p);
315     getWords(file_p);
316 }
```

```
317
318 void hwfarm_extract( hwfarm_task_data* t_data, chFM checkForMobility){
319     int *i = t_data->counter;
320     int *i_max = t_data->counter_max;
321
322     struct db_file_path * db_paths = (struct db_file_path *)t_data->input_data;
323
324     while(*i < *i_max){
325         processFile(db_paths[*i]);
326         (*i)++;
327         checkForMobility();
328     }
329 }
330
331 int isFileExist(const char *filename) {
332     struct stat st;
333     int result = stat(filename, &st);
334     return result == 0;
335 }
336
337 void readStage2Words(char * analyze_file, struct file_word * all_words, int n){
338     if(isFileExist(analyze_file)){
339         FILE* f_analyze;
340         char * tmp_word = (char*)malloc(sizeof(char)*200);
341         if((f_analyze=fopen(analyze_file,"r")) == NULL){
342             printf("Cannot open file(%s).\n", analyze_file);
343         }
344         int tmp_occ = 0;
345         int l = 0;
346         l = fscanf(f_analyze, "%s : %d\n", tmp_word, &tmp_occ);
347         while(l != -1){
348             addWordWithOcc(all_words, 1000, tmp_word, tmp_occ);
349             l = fscanf(f_analyze, "%s : %d\n", tmp_word, &tmp_occ);
350         }
351
352         fclose(f_analyze);
353         free(tmp_word);
354     }
355 }
356
357 void processFileAnalyze(char * analyze_file, struct db_file_path file_p){
358     char * tmp_word = (char*)malloc(sizeof(char)*200);
359
360     struct file_word * all_words = (struct file_word *)malloc(sizeof(struct file_word)*10000);
361     resetAllWords(all_words, 10000);
362     readStage2Words(analyze_file, all_words, 10000);
363
364     FILE* f_stage1_output ;
365     if((f_stage1_output=fopen(file_p.file_output_path,"r")) == NULL){
366         printf("Cannot open file(%s).\n", file_p.file_output_path);
367     }
368
369     char * line = (char*)malloc(sizeof(char)*200);
370     while ( fgets( line, 100, f_stage1_output)){
371         if(!strcmp(line, "List of Words:\n")) {
372             int l = 0;
373             int tmp_occ;
374             l = fscanf(f_stage1_output, "%s : %d\n", tmp_word, &tmp_occ);
375             while(l != -1){
376                 addWordWithOcc(all_words, 1000, tmp_word, tmp_occ);
377                 l = fscanf(f_stage1_output, "%s : %d\n", tmp_word, &tmp_occ);
378             }
379         }
```

```
380     }
381     fclose(f_stage1_output);
382     printStage2WordsToFile(analyze_file, all_words, 10000);
383 
384     free(all_words);
385     free(tmp_word);
386     free(line);
387 }
388 
389 void hwfarm_analyze( hwfarm_task_data* t_data, chFM checkForMobility){
390     int *i = t_data->counter;
391     int *i_max = t_data->counter_max;
392     int t_id = t_data->task_id;
393     char * analyze_file_name = (char*)malloc(sizeof(char)*50);
394     sprintf(analyze_file_name, "db/stage2_output/%d", t_id);
395     struct db_file_path * db_paths = (struct db_file_path *)t_data->input_data;
396     while(*i < *i_max){
397         processFileAnalyze(analyze_file_name, db_paths[*i]);
398         (*i)++;
399         checkForMobility();
400     }
401 }
402 
403 struct db_file_path * assignFilePaths(struct db_file_path * ps, int n){
404     char * orig_path = "db/stage1_input";
405     char * orig_output_path = "db/stage1_output";
406     char *ls_command = (char*)malloc(sizeof(char)*100);
407     sprintf(ls_command, "ls %s -1", orig_path);
408 
409     FILE *fp1;
410     fp1 = popen(ls_command, "r");
411     if(fp1 == 0)
412         perror(ls_command);
413 
414     char *line = (char*)malloc(35 * sizeof(char));
415     int i = 0;
416     while ( fgets( line, 35, fp1)){
417         ps[i].file_id = i;
418         sprintf(ps[i].file_path, "%s/%s", orig_path, line);
419         ps[i].file_path[strlen(ps[i].file_path) - 1] ='\0';
420         sprintf(ps[i].file_output_path, "%s/%s", orig_output_path, line);
421         ps[i].file_output_path[strlen(ps[i].file_output_path) - 1] ='\0';
422         if(++i >= n) break;
423     }
424     pclose(fp1);
425     free(line);
426     free(ls_command);
427     return ps;
428 }
429 
430 int main(int argc, char** argv){
431     initHWFarm(argc,argv);
432 
433     int problem_size = atoi(argv[1]);
434     int tasks = atoi(argv[2]);
435     int mobility = atoi(argv[3]);
436     int chunk = problem_size / tasks;
437 
438     //input
439     struct db_file_path * input_data = NULL;
440     int input_data_size = sizeof(struct db_file_path);
441     int input_data_len = chunk;
442 
```

```
443     //shared
444     void * shared_data = NULL;
445     int shared_data_size = 0;
446     int shared_data_len = 0;
447 
448     //output
449     int *output_data = NULL;
450     int output_data_size = 0;
451     int output_data_len = 0;
452 
453     hwfarm_state main_state;
454     main_state.counter = 0;
455     main_state.max_counter = chunk;
456     main_state.state_data = NULL;
457     main_state.state_len = 0;
458 
459     if(rank == 0){
460        input_data = (struct db_file_path *)malloc(sizeof(struct db_file_path)*problem_size);
461        input_data = assignFilePaths(input_data, problem_size);
462     }
463     //First stage to read the files and extract the important data
464     hwfarm( hwfarm_extract, tasks,
465          input_data, input_data_size, input_data_len,
466          shared_data, shared_data_size, shared_data_len,
467          output_data, output_data_size, output_data_len,
468          main_state, mobility);
469 
470     main_state.counter = 0;
471     main_state.max_counter = chunk;
472 
473     //Second stage to do some analysis
474     hwfarm( hwfarm_analyze, tasks,
475          input_data, input_data_size, input_data_len,
476          shared_data, shared_data_size, shared_data_len,
477          output_data, output_data_size, output_data_len,
478          main_state, mobility);
479 
480     finalizeHWFarm();
481 
482     return 1;
483 }
```

Listing A.6: The findWord application C source code

Appendix B

The HWFarm Skeleton Source Code

This appendix presents the full C code of the HWFarm skeleton. This code shows all details related to mobility support, the cost model and the scheduler.

B.1 The HWFarm Function Header File

```
1  #include <mpi.h>
2  #include <pthread.h>
3
4  int numprocs;
5  int namelen;
6  char processor_name[MPI_MAX_PROCESSOR_NAME];
7  int rank; //process rank
8
9  //For all process
10 double startTime;
11 double startTaskTime;
12 double start_time;
13
14 typedef struct hwfarm_state{
15   int counter;
16   int max_counter;
17   void* state_data;
18   int state_size;
19 } hwfarm_state;
20
21 typedef struct hwfarm_task_data{
22   int task_id;
23   void* input_data;
24   int input_len;
25   void* shared_data;
26   int shared_len;
27   void* state_data;
28   int state_len;
29   void* output_data;
```

```
30    int output_len;
31    int* counter;
32    int* counter_max;
33  } hwfarm_task_data;
34
35  typedef  void(chFM)();
36
37  typedef  void(fp)(hwfarm_task_data*, void(checkForMobility)());
38
39  void initHWFarm(int argc, char ** argv);
40
41  void finalizeHWFarm();
42
43  void hwfarm(fp worker,int tasks,
44        void *input, int inSize,int inLen,
45        void *shared_data, int shared_data_size, int shared_data_len,
46        void *output, int outSize, int outLen, hwfarm_state main_state,
47        int mobility);
```

Listing B.1: The HWFarm Skeleton header file

B.2 The HWFarm Function Source Code

```
1  /*********************************************************************
2  *           HWFarm Skeleton using C, MPI and PThread.
3  *               Turkey Alsalkini & Greg Michaelson
4  *       Heriot-Watt University, Edinburgh, United Kingdom.
5  *********************************************************************/
6  #define _GNU_SOURCE
7  #ifdef _WIN32
8  #define WIN32_LEAN_AND_MEAN
9  #include <windows.h>
10 #else
11 #include <unistd.h>
12 #endif
13
14 #include <errno.h>
15 #include <stdio.h>
16 #include <stdlib.h>
17 #include <math.h>
18 //Helpers
19 #include <string.h>
20 #include <time.h>
21 #include <sys/timeb.h>
22 #include <signal.h>
23 //For RUSAGE
24 #include <sys/time.h>
25 #include <sys/resource.h>
26
27 //Thread gettid
28 #include <sys/types.h>
29 #include <unistd.h>
30 #include <sys/syscall.h>
31 //Top Info
32 #include <sys/sysinfo.h>
33 #include <sys/un.h>
34 #include <unistd.h>
35 //MPI & PThread
```

```
36 #include <mpi.h>
37 #include <pthread.h>
38 //Header File
39 #include "hwfarm.h"
40 /******************* COMMUNICATION TAGS ******************************/
41 //Master to workers Tags
42 #define INIT_LOAD_FROM_WORKER 1
43 #define MOVE_REPORT_FROM_WORKER 2
44 #define LATEST_LOAD_REQUEST 3
45 //#define LOAD_REPORT_FROM_WORKER 6
46 #define RESULTS_FROM_WORKER 7
47 #define MOBILITY_CONFIRMATION_FROM_WORKER 9 //Shared with worker tags
48 #define MOBILITY_NOTIFICATION_FROM_WORKER 10
49 //Worker tags
50 #define LOAD_REQUEST_FROM_MASTER 1
51 #define TERMINATE_THE_WORKER 2
52 #define LOAD_INFO_FROM_MASTER 3
53 #define SENDING_CONFIRMATION_FROM_MASTER 4
54 #define MOBILITY_ACCEPTANCE_FROM_WORKER 5
55 #define UPDATE_LOAD_REPORT_REQUEST 6
56 #define TASK_FROM_MASTER 7
57 #define MOBILITY_REQUEST_FROM_WORKER 8
58 #define TASK_FROM_WORKER 10
59 #define SHARED_DATA_FROM_MASTER 11
60
61 /******************* SKELETON CONSTANTS ******************************/
62 #define MSG_LIMIT 400000000
63 #define ESTIMATOR_BREAK_TIME 3
64 #define NET_LAT_THRESHOLD 1.5
65 #define MAX_MOVES 20        //MAX_MOVES
66 typedef enum {M_TO_W, W_TO_W, W_TO_M} sendType;
67 /******************* GLOBAL VARIABLES ******************************/
68 double start_time;          //holds the start time
69 double end_time;            //holds the end time
70 int isFirstCall = 1;        //@Master to check if hte skeleton is called
71 float Master_FREQ = 0.0;    //Current Node Characterstics
72 int currentCores = 0;       //Current Node Characterstics
73 int moving_task = 0;        //The worker is sending a task now
74 int worker_sending = 0;     //The worker is moving a task now
75 int *masterReceiving;       //To avoid collision at the master
76 int *masterSending;         //To avoid collision at the master
77 /****************** MPI GLOBAL VARIABLES ******************************/
78 MPI_Status status; // store status of a MPI_Recv
79 MPI_Request request; //capture request of a MPI_Isend
80
81 /***************** POSIX GLOBAL VARIABLES ******************************/
82 //@Master
83 pthread_t w_load_report_th;
84 pthread_t w_network_latency_th;
85 //@Worker
86 //Thread to run the worker load agent which collects the
87 //worker load and sends it to the master
88 pthread_t w_load_pth;
89 //Thread to run the worker estimator which is responsible
90 //for estimating the estimated execution time for the tasks
91 //running on the this worker. Then it will send the
92 //move reort to the server to make the moving if necessary.
93 pthread_t w_estimator_pth;
94 //To prevent locking
95 pthread_mutex_t mutex_load_circulating = PTHREAD_MUTEX_INITIALIZER;
96 pthread_mutex_t mutex_w_sending = PTHREAD_MUTEX_INITIALIZER;
97
98 /***************** SKELETON DATA STRUCTURES ************************/
```

```
99  //stats of the moving task to predict the mobility cost
100 struct task_move_stats{
101    double start_move_time;
102    double end_move_time;
103    double move_time;
104    double R_source;
105    double R_dest;
106    double R_1;
107    double R_2;
108    double net_time;
109    int data_size;
110 };
111 //mobile_task: data structure for storing all details about the task
112 struct mobile_task{
113    int m_task_id;                      //tag for task index
114    void * input_data;                  //The input data buffer
115    int input_data_length;              //The input data length
116    int input_data_item_size;           //The input data unit size
117    void * shared_data;                 //The shared data buffer
118    int shared_data_length;             //The shared data length
119    int shared_data_item_size;          //The shared data unit size
120    void * output_data;                 //The output data buffer
121    int output_data_length;             //The output data length
122    int output_data_item_size;          //The output data unit size
123    int counter;                        //The main index iterations
124    int counter_max;                    //The total number of iterations for one task
125    void * state_data;                  //The state buffer
126    int state_data_length;                //The state length
127    long shift;                         //shift value from the start
128    int moves;                          //The numbers of moves for this task
129    int m_dest[MAX_MOVES];              //the workers who processed the task
130    double m_start_time[MAX_MOVES];     //the start times at the workers who processed the task
131    double m_end_time[MAX_MOVES];       //the end times at the workers who processed the task
132    float m_avg_power[MAX_MOVES];       //The average computing power when the task leave the
         machine
133    float m_work_start[MAX_MOVES];      //The start work when the task arrives
134    int moving;                         //label for checking the task movement state
135    int done;                           //label if the task is completed
136    struct task_move_stats move_stats;
137    fp *task_fun;                       //pointer to the task function
138 };
139
140 //data structure to store the run-time task information at the master
141 struct mobile_task_report{
142    int task_id;                        //Task No(ID)
143    int task_status;                    //Current task status(0: waiting; 1: on processing; 2:
         completed; 3: on move )
144    double task_start;                  //The time of start execution
145    double task_end;                    //The time of end execution
146    int task_worker;                    //The current worker where this task runs
147    int mobilities;                     //Number of movements for the task
148    double m_dep_time[MAX_MOVES];       //The departure time from the source worker
149    double m_arr_time[MAX_MOVES];       //The arrival time to the destination worker
150    struct mobile_task * m_task;        //Next record
151 };
152 //data structure to store all tasks at the master
153 struct task_pool{
154    struct mobile_task_report * m_task_report;
155    struct task_pool * next;
156 };
157 //data structure to store a history of the laod state while executing this task
158 struct worker_local_load{
159    float per;
```

```
160     float sec;
161     float load_avg;
162     int est_load_avg;
163     long double w_cpu_uti;
164     int w_running_procs;
165     struct worker_local_load*  next;
166 };
167 //data structure to store details of this task on the worker
168 struct worker_task{
169     int task_id;
170     double w_task_start;
171     double w_task_end;
172     pthread_t task_pth;
173     pthread_t moving_pth;
174     struct mobile_task * m_task;
175     float local_R;
176     int move;
177     int go_move;
178     int go_to;
179     int move_status;
180     struct worker_local_load * w_l_load;
181     struct estimation * estimating_move;
182     struct worker_task * next;
183 };
184 //data structure to store a the network delays at allocation time and the current time
185 struct network_times{
186     double init_net_time;
187     double cur_net_time;
188 };
189 //data structure to store the load state of all workers
190 struct worker_load{
191     int w_rank;
192     char w_name[MPI_MAX_PROCESSOR_NAME];
193     int m_id;
194     int current_tasks;
195     int total_task;
196     int status;           //0:free, 1:working, 2: Requsting, 3: waiting, 4: envolved in moving
197     int w_cores;        //Static metric
198     int w_cache_size;   //Static metric
199     float w_cpu_speed; //Static metric
200     float w_load_avg_1;
201     float w_load_avg_2;
202     int estimated_load;
203     long double w_cpu_uti_1;
204     long double w_cpu_uti_2;
205     int w_running_procs;
206     int locked;
207     struct network_times net_times;
208 };
209 //data structure to store the move report issued by the estimator agent
210 struct worker_move_report{
211     int w_id;
212     int num_of_tasks;
213     int * list_of_tasks;
214 };
215 //data structure to store details when a worker becomes busy in receiving a task from a worker
216 struct worker_hold{
217     int on_hold;          //set to indicate that this worker is on hold to complete the move from
        the source worker
218     int holded_on;        //number of tasks which the worker is waiting for
219     int holded_from;      //the worker who i am holded to
220     float hold_time;      //the time of hold. for cancelation if the request timed out
221 };
```

```
222 //data structure to store refrences fro other structures in the worker
223 struct worker_load_task{
224    struct worker_hold hold;
225    pid_t worker_tid;
226    pid_t status_tid;
227    pid_t estimator_tid;
228    struct worker_load w_local_loads;
229    struct worker_load * w_loads;
230    struct worker_task * w_tasks;
231    struct worker_move_report * move_report;
232 };
233 //data structure to store the report of the estimated times
234 struct estimation{
235    float * estimation_costs;
236    int chosen_dest;
237    float gain_perc;
238    int done;
239    int on_dest_recalc;
240 };
241 //data structure to store the estimated times on remote workers
242 struct other_estimated_costs{
243    int w_no;
244    float * costs;
245    float move_cost;
246 };
247 //data structure to store detailed report of estimated times for this task
248 struct estimated_cost{
249    int task_no;
250    float cur_EC;
251    float spent_here;
252    float *cur_EC_after;
253    struct other_estimated_costs* other_ECs;
254    int to_w;
255    float to_EC;
256 };
257
258 /******************** GLOBAL DATA STRUCTURES *************************/
259 ///-----Worker--------
260 struct worker_load_task * w_l_t = NULL;
261 struct worker_load * workers_load_report = NULL;
262 struct worker_task * w_tasks;
263 ///-----Master--------
264 struct worker_load * w_load_report = 0;
265 struct worker_load * w_load_report_tmp = 0;
266
267 /********************** LINUX/OS FUNCTIONS ***************************/
268
269 void systemCall(char* b,char* res){
270    FILE *fp1;
271    char *line = (char*)malloc(130 * sizeof(char));
272    fp1 = popen(b, "r");
273    if(fp1 == 0)
274       perror(b);
275    res[0]='\0';
276    while ( fgets( line, 130, fp1))
277     strcat(res, line);
278    res[strlen(res)-1]='\0';
279    pclose(fp1);
280    free(line);
281    return;
282 }
283 void systemCallNoRes(char* b){
284    //Execute System call
```

```
285     FILE *fp;
286     fp = popen(b, "r");
287     pclose(fp);
288 }
289 //send ping message to the selected worker
290 double sendPing(char * node_name){
291     char * pre_ping_command = "ping %s -c 1 | grep \"rtt\" | awk '{split($0,a,\" \"); print a
          [4]}' | awk '{split($0,b,\"/\"); print b[2]}'";
292     char *ping_command = (char*)malloc(sizeof(char)*200);
293     sprintf(ping_command, pre_ping_command, node_name);
294     char * rtt_latency_str = (char*)malloc(sizeof(char)*20);
295     systemCall(ping_command, rtt_latency_str);
296     double net_latency = atof(rtt_latency_str);
297     if(net_latency != 0.0){
298         free(ping_command);
299         free(rtt_latency_str);
300         return net_latency;
301     }else{
302         free(ping_command);
303         free(rtt_latency_str);
304         return 0.0;
305   }
306 }
307
308 /******************** LOAD STATE FUNCTIONS ***************************/
309
310 int contains(char target[],int m, char source[] ,int n){
311     int i,j=0;
312     for(i=0;i<n;i++){
313         if(target[j] == source[i])j++;
314         else j=0;
315         if(j == m)return 1;
316     }
317     return 0;
318 }
319
320 float getCoresFreq(){
321     FILE *f;
322     int LINE_MAX = 128;
323     char *line = (char*)malloc(LINE_MAX * sizeof(char));
324     char *tmp = (char*)malloc(10 * sizeof(char));
325     float total_cores_freq = 0;
326
327     f = fopen("/proc/cpuinfo","r");
328     if(f == 0){
329         perror("Could open the file :/proc/cpuinfo");
330         return 0;
331     }
332
333     float core_freq = 0, min_core_freq = 0;
334     int cores_cnt = 0;
335     char c;
336     while(fgets(line, LINE_MAX, f)){
337         if(contains("cpu MHz", 7, line, LINE_MAX)){
338             sscanf(line, "%s %s %c %f\n", tmp, tmp, &c, &core_freq);
339             if(cores_cnt == 0)
340                 min_core_freq = core_freq;
341             else if(min_core_freq > core_freq)
342                 min_core_freq = core_freq;
343             total_cores_freq += core_freq;
344             cores_cnt++;
345         }
346     }
```

```
347     fclose(f);
348     free(tmp);
349     free(line);
350     return min_core_freq * cores_cnt;
351 }
352 
353 int getNumberOfCores(){
354     long nprocs = -1;
355     long nprocs_max = -1;
356     #ifdef _WIN32
357         #ifndef _SC_NPROCESSORS_ONLN
358             SYSTEM_INFO info;
359             GetSystemInfo(&info);
360             #define sysconf(a) info.dwNumberOfProcessors
361             #define _SC_NPROCESSORS_ONLN
362         #endif
363     #endif
364     #ifdef _SC_NPROCESSORS_ONLN
365         nprocs = sysconf(_SC_NPROCESSORS_ONLN);
366         if (nprocs < 1){
367             fprintf(stderr, "Could not determine number of CPUs online:\n%s\n",
368             strerror (errno));
369             return nprocs;
370         }
371         nprocs_max = sysconf(_SC_NPROCESSORS_CONF);
372         if (nprocs_max < 1){
373             fprintf(stderr, "Could not determine number of CPUs configured:\n%s\n",
374             strerror (errno));
375             return nprocs;
376         }
377         return nprocs;
378     #else
379         fprintf(stderr, "Could not determine number of CPUs");
380         return nprocs;
381     #endif
382 }
383 
384 int getProcessState(int p_id, int is_task, int t_id){
385     FILE *f;
386     char *line = (char*)malloc(1000 * sizeof(char));
387     char * stateFile = (char*)malloc(sizeof(char)*200);
388     if(is_task == 1)
389         sprintf(stateFile, "/proc/%u/task/%u/stat", p_id, t_id);
390     else
391         sprintf(stateFile, "/proc/%u/stat", p_id);
392     f = fopen(stateFile,"r");
393     if(f == 0)
394         return 0;
395     int state = 0, i = 0;
396     do{
397         if(strlen(line) == 1){
398             char c = *((char *)line);
399             if((c == 'S') || (c == 'D') || (c == 'T') || (c == 'W') || (c == 'Z')){
400                 state = 0;
401                 break;
402             }
403             if(c == 'R'){
404                 state = 1;
405                 break;
406             }
407         }
408     }while(i++ != 10);
409     fclose(f);
```

```
410     free(line);
411     free(stateFile);
412     return state;
413 }
414 
415 int getRunningProc(){
416     FILE *f;
417     char *line = (char*)malloc(1000 * sizeof(char));
418     int run_proc = 0;
419 
420     f = fopen("/proc/stat","r");
421     if(f == 0)
422         perror("/proc/stat");
423 
424     int l = 0, numOfI = 0;
425     do{
426         l = fscanf(f, "%s\n", line);
427         if(strcmp(line, "procs_running") == 0){
428             numOfI = fscanf(f, "%d\n", &run_proc);
429             break;
430         }
431     }while(l != 0);
432     fclose(f);
433     free(line);
434     return run_proc;
435 }
436 
437 void getCPUValues(long double * a){
438     FILE *f;
439     f = fopen("/proc/stat","r");
440     int r = -1;
441     r = fscanf(f,"%*s %Lf %Lf %Lf %Lf %Lf",&a[0],&a[1],&a[2],&a[3],&a[4]);
442     fclose(f);
443 }
444 
445 double calculateCPUUti(long double * a, long double * b){
446     long double user = b[0] - a[0];
447     long double nice = b[1] - a[1];
448     long double system = b[2] - a[2];
449     long double idle = b[3] - a[3];
450     long double wa = b[4] - a[4];
451     long double total = user + nice + system + idle + wa;
452     long double per = 0.0;
453     if(total != 0.0)
454         per = (( user + nice + system) * 100) / total;
455     return per;
456 }
457 
458 float getLoad(){
459     struct sysinfo sys_info;
460     if(sysinfo(&sys_info) != 0)
461         perror("sysinfo");
462     return sys_info.loads[0]/65536.0;
463 }
464 
465 
466 void setLocalLoadInfo(long double * a, long double * b, long double * per, int *rp, float *
        load_avg){
467     double load_overhead_1 = 0.0;
468     double load_overhead_2 = 0.0;
469     double load_overhead_sum = 0.0;
470     long double tmp_per = 0;
471     int tmp_rp = 0;
```

```
472     int READ_COUNT = 5;
473     int READ_DELAY = 1000000 /    READ_COUNT;
474     int i=0;
475     for(i = 0; i < READ_COUNT; i++){
476        usleep(READ_DELAY);
477        a[0] = b[0];
478        a[1] = b[1];
479        a[2] = b[2];
480        a[3] = b[3];
481        a[4] = b[4];
482        load_overhead_1 = MPI_Wtime();
483        getCPUValues(b);
484        tmp_per += calculateCPUUti(a, b);
485        tmp_rp += getRunningProc()-1;
486        load_overhead_2 = MPI_Wtime();
487        load_overhead_sum += (load_overhead_2 - load_overhead_1);
488     }
489
490     *per = tmp_per / READ_COUNT;
491     *rp = tmp_rp / READ_COUNT;
492     load_overhead_1 = MPI_Wtime();
493     *load_avg = getLoad();
494     load_overhead_2 = MPI_Wtime();
495  }
496
497  /********************* SKELETON FUNCTIONS ***************************/
498  struct task_pool * addTasktoPool(
499      struct task_pool * pool, int task_no, void * input_data, int input_data_len,
500      int input_data_unit_size, void * output_data, int output_data_len,
501      int output_data_unit_size, int tag, int shift, void * state,
502      int state_size, int main_index, int main_index_max){
503
504     struct task_pool * pl = pool;
505     if(pool == 0){
506        pool = (struct task_pool *)malloc(sizeof(struct task_pool));
507        pool->m_task_report = (struct mobile_task_report *)malloc(sizeof(struct mobile_task_report
       ));
508        pool->m_task_report->task_id = task_no;
509        pool->m_task_report->task_status = 0;
510        pool->m_task_report->task_start = 0;
511        pool->m_task_report->task_end = 0;
512        pool->m_task_report->task_worker = 0;
513        pool->m_task_report->mobilities = 0;
514        pool->m_task_report->m_task = (struct mobile_task *)malloc(sizeof(struct mobile_task));
515        if(input_data != NULL){
516           pool->m_task_report->m_task->input_data = input_data + shift;
517           pool->m_task_report->m_task->input_data_length = input_data_len;
518           pool->m_task_report->m_task->input_data_item_size = input_data_unit_size;
519        }
520        pool->m_task_report->m_task->output_data = output_data;
521        pool->m_task_report->m_task->output_data_length = output_data_len;
522        pool->m_task_report->m_task->output_data_item_size = output_data_unit_size;
523        pool->m_task_report->m_task->m_task_id = tag;
524        pool->m_task_report->m_task->shift = shift;
525        pool->m_task_report->m_task->state_data = state;
526        pool->m_task_report->m_task->state_data_length = state_size;
527        pool->m_task_report->m_task->counter = main_index;
528        pool->m_task_report->m_task->counter_max = main_index_max;
529        pool->m_task_report->m_task->moves = 0;
530        pool->m_task_report->m_task->done = 0;
531        pool->m_task_report->m_task->moving = 0;
532        pool->next = 0;
533     }else{
```

```
534         while(pl->next != 0)
535             pl = pl->next;
536 
537         pl->next = (struct task_pool *)malloc(sizeof(struct task_pool));
538         pl = pl->next;
539         pl->m_task_report = (struct mobile_task_report *)malloc(sizeof(struct mobile_task_report))
        ;
540         pl->m_task_report->task_id = task_no;
541         pl->m_task_report->task_status = 0;
542         pl->m_task_report->task_start = 0;
543         pl->m_task_report->task_end = 0;
544         pl->m_task_report->task_worker = 0;
545         pl->m_task_report->mobilities = 0;
546         pl->m_task_report->m_task = (struct mobile_task *)malloc(sizeof(struct mobile_task));
547         if(input_data != NULL){
548             pl->m_task_report->m_task->input_data = input_data + shift;
549             pl->m_task_report->m_task->input_data_length = input_data_len;
550             pl->m_task_report->m_task->input_data_item_size = input_data_unit_size;
551         }
552         pl->m_task_report->m_task->output_data = output_data;
553         pl->m_task_report->m_task->output_data_length = output_data_len;
554         pl->m_task_report->m_task->output_data_item_size = output_data_unit_size;
555         pl->m_task_report->m_task->m_task_id = tag;
556         pl->m_task_report->m_task->shift = shift;
557         pl->m_task_report->m_task->state_data = state;
558         pl->m_task_report->m_task->state_data_length = state_size;
559         pl->m_task_report->m_task->counter = main_index;
560         pl->m_task_report->m_task->counter_max = main_index_max;
561         pl->m_task_report->m_task->moves = 0;
562         pl->m_task_report->m_task->done = 0;
563         (pl->m_task_report->m_task->moving) = 0;
564         pl->next = 0;
565     }
566     return pool;
567 }
568 
569 struct task_pool * create_task_pool(
570       int tasks, void* input, int input_len, int input_size, void* output,
571       int output_len, int output_size,void* state, int state_size,
572       int main_index, int chunk_size){
573 
574     int task_i = 0;
575     int task_shift = 0;
576     struct task_pool * pool = 0;
577     while(task_i < tasks){
578         task_shift = (task_i * input_len) * input_size;
579         pool = addTasktoPool(pool, task_i, input, input_len, input_size,
580               output, output_len, output_size, task_i, task_shift,
581               state, state_size, main_index, chunk_size);
582         task_i++;
583     }
584     return pool;
585 }
586 
587 ///This function is used to check the mobility and perform a checkpointing
588 ///if there is a need to transfer this computation
589 void checkForMobility(){
590     pthread_t pth_id = pthread_self();
591     if(w_tasks == NULL) return;
592     struct worker_task * wT = w_tasks->next;
593     for(;wT!=0;wT=wT->next){
594         if(pth_id == wT->task_pth)
595             if((wT->move == 1) && (moving_task == 0)){
```

```
596                 wT->go_move = 1;
597                 while(wT->move_status == 0) usleep(1);
598                 if(wT->move_status == 1)
599               pthread_exit(NULL);
600              }
601       }
602    }
603
604    void printMobileTask(struct mobile_task* mt){
605       printf("Task id: %d @ %d\n----------------------------------------------------\n", mt->m_task_id,
          rank);
606       printf("Input:  (len: %d) - (u_size: %d)\n", mt->input_data_length, mt->input_data_item_size)
          ;
607       printf("Output: (len: %d) - (u_size: %d)\n", mt->output_data_length, mt->
          output_data_item_size);
608       printf("State: (u_size: %d)\n", mt->state_data_length);
609       printf("Main Counter: (init: %d) - (max: %d)\n", mt->counter, mt->counter_max);
610
611       double final_ex_time = 0.0;
612       int i;
613       for(i=0;i<mt->moves; i++){
614          final_ex_time += mt->m_end_time[i] - mt->m_start_time[i];
615          printf("--@ %d (F: %f - to: %f [%f])\n", mt->m_dest[i], mt->m_start_time[i], mt->
          m_end_time[i], mt->m_end_time[i] - mt->m_start_time[i]);
616       }
617       printf("--@ X (Total Ex Time: %f)\n", final_ex_time);
618       for(i=0;i<mt->moves; i++)
619          printf("%f\n%f\n", mt->m_start_time[i], mt->m_end_time[i]);
620       printf("\n----------------------------------------------------\n");
621    }
622
623    void printTaskPool(struct task_pool * pool){
624       struct task_pool * p = pool;
625       while(p != 0){
626          printMobileTask(p->m_task_report->m_task);
627          p = p->next;
628       }
629    }
630
631    void sendMobileMultiMsgs(void *input, int dataLen, int limit, int proc, int tag){
632       if(dataLen == 0) return;
633       int msgCount = (dataLen/limit);
634       if((dataLen % limit) != 0) msgCount++;
635       int msgSize;
636       int i=0;
637       MPI_Ssend(&msgCount, 1, MPI_INT, proc, tag, MPI_COMM_WORLD);
638       for(i = 0; i<msgCount; i++){
639          if(dataLen < limit)
640             msgSize = dataLen;
641          else
642             msgSize = limit;
643          MPI_Ssend(input + (i * limit), msgSize, MPI_CHAR, proc, tag + i + 1, MPI_COMM_WORLD);
644          dataLen = dataLen - msgSize;
645       }
646    }
647
648    void recvMobileMultiMsgs(void * input, int dataLen, int limit, int source, int tag){
649       if(dataLen == 0) return;
650       int msgSize ;
651       int msgCount;
652       int i=0;
653       MPI_Recv(&msgCount, 1 , MPI_INT, source, tag, MPI_COMM_WORLD, &status);
654       for(i = 0; i<msgCount; i++){
```

```
655         if(dataLen < limit)
656             msgSize = dataLen;
657         else
658             msgSize = limit;
659         MPI_Recv(input + (i * limit), msgSize, MPI_CHAR, source, tag + i + 1, MPI_COMM_WORLD, &
        status);
660         dataLen = dataLen - msgSize;
661     }
662 }
663
664 int getTaskResultSize(struct mobile_task* w_mt){
665     int task_struct_size = sizeof(struct mobile_task);
666     int task_output_size = w_mt->input_data_length*w_mt->input_data_item_size;
667     return task_struct_size + task_output_size;
668 }
669
670 int getInitialTaskSize(struct mobile_task* w_mt){
671     int task_struct_size = sizeof(struct mobile_task);
672     int task_input_size = w_mt->input_data_length*w_mt->input_data_item_size;
673     int task_state_size = w_mt->state_data_length;
674     return task_struct_size + task_input_size + task_state_size;
675 }
676
677 int getTotalTaskSize(struct mobile_task* w_mt){
678     int task_output_size = w_mt->output_data_length*w_mt->output_data_item_size;
679     int task_init_size = getInitialTaskSize(w_mt);
680     return task_output_size + task_init_size;
681 }
682
683 void sendMobileTask(struct mobile_task* mt, int w, sendType t){
684     int send_code = 0;
685
686     if(t == W_TO_W)
687         send_code = TASK_FROM_WORKER;
688     else if(M_TO_W)
689         send_code = TASK_FROM_MASTER;
690     else if(W_TO_M)
691         send_code = RESULTS_FROM_WORKER;
692
693     if(t == W_TO_M)
694         worker_sending = 0;
695
696     MPI_Ssend(&send_code, 1, MPI_INT, w, send_code, MPI_COMM_WORLD);
697
698     if(t == W_TO_M)
699         while(worker_sending == 0) usleep(1);
700
701     if(t == M_TO_W){
702         while(*(masterReceiving + (w) - 1) == 1) usleep(1);
703         *(masterSending + w - 1) = 1;
704     }
705
706     if(t == W_TO_M)
707         MPI_Ssend(&(mt->m_task_id), 1, MPI_INT, w, send_code, MPI_COMM_WORLD);
708
709     MPI_Ssend(mt, sizeof(struct mobile_task), MPI_CHAR, w, send_code, MPI_COMM_WORLD);
710
711     if(t != W_TO_M)
712         sendMobileMultiMsgs(mt->input_data, mt->input_data_length*mt->input_data_item_size,
        MSG_LIMIT, w, send_code);
713     if(t != M_TO_W)
714         sendMobileMultiMsgs(mt->output_data, mt->output_data_length*mt->output_data_item_size,
        MSG_LIMIT, w, send_code);
```

```
715     if(t != W_TO_M)
716         sendMobileMultiMsgs(mt->state_data, mt->state_data_length, MSG_LIMIT, w, send_code);
717     if(t == M_TO_W)
718         *(masterSending + w - 1) = 0;
719 }
720
721 void sendMobileTaskM(struct mobile_task_report* mtr, int w){
722     mtr->m_task->move_stats.start_move_time = MPI_Wtime();
723     mtr->m_task->move_stats.R_source = Master_FREQ;
724     sendMobileTask(mtr->m_task, w, M_TO_W);
725     mtr->task_status = 1;
726     mtr->task_start = MPI_Wtime();
727     mtr->task_worker = w;
728 }
729
730 void* recvSharedData(void* shared_data, int * w_shared_len, int source, int send_code){
731     MPI_Status status;
732     int shared_len;
733     MPI_Recv(&shared_len, 1, MPI_INT, source, send_code, MPI_COMM_WORLD, &status);
734     *w_shared_len = shared_len;
735     if(shared_len != 0){
736         shared_data = (void*)malloc(shared_len);
737         recvMobileMultiMsgs(shared_data, shared_len, MSG_LIMIT, source, send_code);
738         return shared_data;
739     }
740     return NULL;
741 }
742
743 void recvMobileTask(struct mobile_task* w_mt, int source, sendType t, int send_code){
744     MPI_Status status;
745     void * p_input;
746     void * p_state;
747     if(t == W_TO_M){
748         p_input = w_mt->input_data;
749         p_state = w_mt->state_data;
750     }
751
752     MPI_Recv(w_mt, sizeof(struct mobile_task), MPI_CHAR, source, send_code, MPI_COMM_WORLD,&
          status);
753
754     if(t != W_TO_M){
755         //Allocating & receiving input data
756         w_mt->input_data = (void*)malloc(w_mt->input_data_length*w_mt->input_data_item_size);
757         recvMobileMultiMsgs(w_mt->input_data, w_mt->input_data_length*w_mt->input_data_item_size,
          MSG_LIMIT, source, send_code);
758     }else
759         w_mt->input_data = p_input;
760     //Allocating & receiving output data
761     w_mt->output_data = (void*)malloc(w_mt->output_data_length*w_mt->output_data_item_size);
762     if(t != M_TO_W)
763         recvMobileMultiMsgs(w_mt->output_data, w_mt->output_data_length*w_mt->
          output_data_item_size, MSG_LIMIT, source, send_code);
764     if(t != W_TO_M){
765         //Allocating & receiving states data
766         w_mt->state_data = (void*)malloc(w_mt->state_data_length);
767         recvMobileMultiMsgs(w_mt->state_data, w_mt->state_data_length, MSG_LIMIT, source,
          send_code);
768     }else
769         w_mt->state_data = p_state;
770
771     if(t != W_TO_M){
772         w_mt->moves++;
773         w_mt->m_dest[w_mt->moves-1] = rank;
```

```
774     }
775 }
776 //recevie results of the task
777 void recvMobileTaskM(struct task_pool* t_p, int w, int msg_code){
778     int task_id = -1;
779     MPI_Recv(&task_id, 1, MPI_INT, w, msg_code, MPI_COMM_WORLD, &status);
780     struct task_pool * p = t_p;
781     while( p != NULL){
782         if(p->m_task_report->task_id == task_id){
783             recvMobileTask(p->m_task_report->m_task, w, W_TO_M, msg_code);
784             p->m_task_report->task_status = 2;
785             p->m_task_report->task_end = MPI_Wtime();
786             p->m_task_report->task_worker = 0;
787             break;
788         }
789         p = p->next;
790     }
791 }
792
793 void recvMsgCode(int *recv_w,int *msg_code){
794     MPI_Request req;
795     int msgType = -1;
796     int flag = 0;
797     MPI_Status status;
798     ///Non-Blocking MPI_Irecv
799     MPI_Irecv(&msgType, 1, MPI_INT, MPI_ANY_SOURCE, MPI_ANY_TAG, MPI_COMM_WORLD, &req);
800     do {
801         MPI_Test(&req, &flag, &status);
802         usleep(10);
803     } while (flag != 1);
804     *recv_w = status.MPI_SOURCE;
805     *msg_code = status.MPI_TAG;
806 }
807
808 void *workerMobileTask(void *arg){
809     struct mobile_task *w_mt = ((struct mobile_task *)arg);
810     w_mt->m_start_time[w_mt->moves-1] = MPI_Wtime();
811     int i = w_mt->counter;
812     float Wd_before = ((i * 100) / (float)w_mt->counter_max);
813     w_mt->m_work_start[w_mt->moves-1] = Wd_before;
814
815     hwfarm_task_data * t_data = (hwfarm_task_data *)malloc(sizeof(hwfarm_task_data));
816     t_data->input_data = w_mt->input_data;
817     t_data->input_len = w_mt->input_data_length;
818     t_data->shared_data = w_mt->shared_data;
819     t_data->shared_len = w_mt->shared_data_length;
820     t_data->state_data = w_mt->state_data;
821     t_data->state_len = w_mt->state_data_length;
822     t_data->output_data = w_mt->output_data;
823     t_data->output_len = w_mt->output_data_length;
824     t_data->counter = &w_mt->counter;
825     t_data->counter_max = &w_mt->counter_max;
826     t_data->task_id = w_mt->m_task_id;
827
828     w_mt->task_fun( t_data, checkForMobility);
829     w_mt->done = 1;
830     w_mt->m_end_time[w_mt->moves-1] = MPI_Wtime();
831
832     pthread_mutex_lock( &mutex_w_sending );
833     sendMobileTask(w_mt, 0, W_TO_M);
834     pthread_mutex_unlock( &mutex_w_sending );
835
836     free(w_mt->state_data);
```

```
837     free(w_mt->output_data);
838     free(w_mt->input_data);
839 
840     return NULL;
841 }
842 
843 float getActualRunningprocessors(float cpu_uti, int est_load_avg, int running_processes, int
        cores){
844     float np_per = -1;
845     if(cpu_uti < 75)
846         np_per = cpu_uti ;
847     else{
848         if(running_processes <= cores)
849             np_per = cpu_uti;
850         else
851             np_per = (cpu_uti + ((running_processes) * 100) / (cores * 1.0)) / 2;
852     }
853     float base = 100 / (cores * 1.0);
854     int np = (int)(np_per / base);
855     if(np < (np_per / base))
856         np++;
857     return (np_per/base);
858 }
859 
860 float getActualRelativePower(float P, float cpu_uti, int est_load_avg, int running_processes,
        int cores, int added_np, int worker){
861     float np_f = getActualRunningprocessors( cpu_uti,  est_load_avg,  running_processes, cores);
862     //Add/subtract the number of process
863     if(added_np != 0)
864         np_f += added_np;
865     float Rhn = P/np_f;
866     float MAX_R = P/cores;
867     if(Rhn > MAX_R)
868         Rhn = MAX_R;
869     return Rhn;
870 }
871 
872 float getRForWorker(struct worker_load_task *w_l_t, int worker){
873     float remote_power = (w_l_t->w_loads + worker - 1)->w_cpu_speed;
874     float remote_cpu_uti = (w_l_t->w_loads + worker - 1)->w_cpu_uti_2;
875     int remote_ext_load_avg = (w_l_t->w_loads + worker - 1)->estimated_load;
876     int remote_running_procs = (w_l_t->w_loads + worker - 1)->w_running_procs;
877     int remote_cores = (w_l_t->w_loads + worker - 1)->w_cores;
878     float R = getActualRelativePower(remote_power, remote_cpu_uti, remote_ext_load_avg,
        remote_running_procs + 1, remote_cores, 0, (w_l_t->w_loads + worker - 1)->w_rank);
879     return R;
880 }
881 
882 float getPredictedMoveTime(struct mobile_task* w_mt, struct worker_load_task * w_l_t, int worker
        ){
883     float R_1 = w_mt->move_stats.R_source;
884     if(R_1 > w_mt->move_stats.R_dest)
885         R_1 = w_mt->move_stats.R_dest;
886     w_mt->move_stats.R_1 = R_1;
887     int data_size_1 = w_mt->move_stats.data_size;
888     double net_time_1 = w_l_t->w_loads->net_times.init_net_time;
889     double move_time_1 = w_mt->move_stats.move_time;
890     int data_size_2 = getTotalTaskSize(w_mt);
891     double net_time_2 = w_l_t->w_loads->net_times.cur_net_time;
892     float R_2_s = getRForWorker(w_l_t, rank);
893     float R_2_d = getRForWorker(w_l_t, worker);
894     float R_2 = R_2_s;
895     if(R_2 > R_2_d)
```

```
896         R_2 = R_2_d;
897     w_mt->move_stats.R_2 = R_2;
898 
899     float W_DS = 1.023;
900     float W_R = 1.04;
901     float W_L = 0.907;
902 
903     double R_effect = pow((R_1 / R_2), W_R);
904     double SD_effect = pow((1.0*data_size_2 / data_size_1), W_DS);
905 
906     double net_time_mobility = (net_time_2 < NET_LAT_THRESHOLD) ? NET_LAT_THRESHOLD : net_time_2;
907     double net_time_a = (net_time_1 < NET_LAT_THRESHOLD) ? NET_LAT_THRESHOLD : net_time_1;
908     double Net_effect = pow((net_time_mobility / net_time_a), W_L);
909 
910     return (R_effect * SD_effect * Net_effect) * move_time_1;
911 }
912 
913 void taskOutput(struct task_pool* t_p, void* output, int outLen, int outSize){
914     int task_i = 0, output_i = 0, task_output_i = 0;
915     int output_shift;
916     struct task_pool * p = t_p;
917     while( p != NULL){
918         output_shift = (task_i * outLen) * outSize;
919         for(task_output_i = 0; task_output_i < outLen*outSize; task_output_i++)
920             *((char*)output + output_i++) = *((char*)p->m_task_report->m_task->output_data +
      task_output_i);
921         p = p->next;
922         task_i++;
923     }
924 }
925 
926 void printWorkerLoadReport(struct worker_load * report, int n){
927     int i;
928     printf("
       ------------------------------------------------------------------------------------------
       n");
929     printf("[M/W]- W | no | ts | tot_t | Locked | s | cores | cache |  CPU Freq  | l.avg1 | l.
       avg2 | est | uti.1 | uti.2 | run_pro [%.3f] \n", (MPI_Wtime() - startTime));
930     printf("
       ------------------------------------------------------------------------------------------
       n");
931     for(i=1; i<n; i++){
932         printf("[%d]- %3d | %2d | %2d |  %2d   | %c |  %c  |  %2d   |  %2d   | %.2f  | "
933                 " %2.2f  |  %2.2f  | %2d  | %3.2Lf  |  %3.2Lf | %d\n",
934                 rank, report[i-1].w_rank, report[i-1].m_id,
935                 report[i-1].current_tasks, report[i-1].total_task, (report[i-1].locked == 1 ? 'Y' :
       'N'),
936                 ((report[i-1].status == 1) ? 'B' : ((report[i-1].status == 4) ? 'M' : 'F')), report
       [i-1].w_cores, report[i-1].w_cache_size,
937                 report[i-1].w_cpu_speed, report[i-1].w_load_avg_1, report[i-1].w_load_avg_2, report
       [i-1].estimated_load,
938                 report[i-1].w_cpu_uti_1, report[i-1].w_cpu_uti_2, report[i-1].w_running_procs);
939     }
940     printf("
       ------------------------------------------------------------------------------------------
       n");
941 }
942 
943 void updateWorkerStatus(struct worker_load * report, int n, int worker, int new_status){
944     int i;
945     for(i=1; i<n; i++)
946         if(report[i-1].w_rank == worker)
947             report[i-1].status = new_status;
```

```
948 }
949
950 void updateWorkerStatusMoving(struct worker_load * report, int n, int source, int dest){
951     updateWorkerStatus(report, n, source, 4);
952     updateWorkerStatus(report, n, dest, 4);
953 }
954
955 void updateWorkerStatusWorking(struct worker_load * report, int n, int source, int dest){
956     updateWorkerStatus(report, n, source, 1);
957     updateWorkerStatus(report, n, dest, 1);
958 }
959
960 void recvMovingNotification(struct worker_load * report, int n, int w_source, int msg_code){
961     int* data = (int*)malloc(sizeof(int)*2);
962     MPI_Recv(data, 2, MPI_INT, w_source, msg_code, MPI_COMM_WORLD, &status);
963     updateWorkerStatusMoving(report, n, w_source, *(data+1));
964 }
965
966 //Get the worker who will recieve the next task
967 void getValidWorker(int * tasksPerWorker, int n, int *w){
968     int w_i = 0;
969     for(w_i = 0; w_i < n; w_i++)
970         if(tasksPerWorker[w_i] > 0){
971             tasksPerWorker[w_i]--;
972             *w = w_i+1;
973             return;
974         }
975 }
976
977 struct mobile_task_report * getReadyTask( struct task_pool* t_p){
978     struct task_pool * p = t_p;
979     while( p != NULL){
980         if(p->m_task_report->task_status == 0)
981             return p->m_task_report;
982         p = p->next;
983     }
984     return NULL;
985 }
986
987 ///Send terminator message to the finished worker
988 void terminateWorker(int w){
989     int msg_code = TERMINATE_THE_WORKER;
990     MPI_Send(&msg_code, 1, MPI_INT, w, msg_code, MPI_COMM_WORLD);
991 }
992
993 ///Send Terminator message to all processes
994 void terminateWorkers(int ws){
995     int i=0;
996     for( i=1; i < ws; i++)
997         terminateWorker(i);
998 }
999
1000 struct worker_task* newWorkerTask(struct worker_task * w_t_header, struct worker_task * w_t){
1001     if(w_t_header == NULL){
1002         w_t_header = w_t;
1003         w_t_header->next = NULL;
1004         return w_t_header;
1005     }
1006     struct worker_task * p = w_t_header;
1007     while(p->next != NULL)
1008         p = p->next;
1009     p->next = w_t;
1010     p->next->next = NULL;
```

```
1011    return w_t_header;
1012 }
1013
1014 void sendInitialWorkerLoad(struct worker_load * l_load, int master){
1015    int msg_code = INIT_LOAD_FROM_WORKER;
1016    MPI_Send(&msg_code, 1, MPI_INT, master, msg_code, MPI_COMM_WORLD);
1017    MPI_Send(l_load, sizeof(struct worker_load), MPI_CHAR, master, msg_code, MPI_COMM_WORLD);
1018 }
1019
1020 void sendWorkerLoad(void * d, int load_info_size, int master){
1021    int msg_code = 1;
1022    MPI_Send(&msg_code, 1, MPI_INT, master, msg_code, MPI_COMM_WORLD);
1023    MPI_Send( &load_info_size, 1, MPI_INT, master, msg_code, MPI_COMM_WORLD);
1024    MPI_Send( d, load_info_size, MPI_CHAR, master, msg_code, MPI_COMM_WORLD);
1025 }
1026
1027 void obtainLatestLoad(int master){
1028    int msg_code = LATEST_LOAD_REQUEST;
1029    MPI_Send(&msg_code, 1, MPI_INT, master, msg_code, MPI_COMM_WORLD);
1030 }
1031
1032 void sendMoveReport(int* move_report, int report_size, int target){
1033    int msg_code = MOVE_REPORT_FROM_WORKER;
1034    MPI_Send(&msg_code, 1, MPI_INT, target, msg_code, MPI_COMM_WORLD);
1035    MPI_Send( &report_size, 1, MPI_INT, target, msg_code, MPI_COMM_WORLD);
1036    MPI_Send( move_report, report_size, MPI_INT, target, msg_code, MPI_COMM_WORLD);
1037 }
1038
1039 void sendMoveReportToWorker(int target, int numTasks, int load_no){
1040    int msg_code = MOBILITY_REQUEST_FROM_WORKER;
1041    MPI_Send(&msg_code, 1, MPI_INT, target, msg_code, MPI_COMM_WORLD);
1042    int*msg_numTasks_load_no = (int*)malloc(sizeof(int)*2);
1043    *msg_numTasks_load_no = numTasks;
1044    *(msg_numTasks_load_no + 1) = load_no;
1045    MPI_Send( msg_numTasks_load_no, 2, MPI_INT, target, msg_code, MPI_COMM_WORLD);
1046    free(msg_numTasks_load_no);
1047 }
1048
1049 void sendMoveReportToWorkers(struct worker_move_report * w_m_report, struct worker_load * report
       ){
1050    int i_w = 0;
1051    for(;i_w<numprocs-1; i_w++){
1052       if(i_w != rank-1){
1053          if((w_m_report + i_w)->num_of_tasks > 0){
1054             int w = (w_m_report + i_w)->w_id;
1055             sendMoveReportToWorker((w_m_report + i_w)->w_id+1, (w_m_report + i_w)->num_of_tasks,
       (report + w)->m_id);
1056          }
1057       }
1058    }
1059 }
1060
1061 //type: 1 -- mobile request recieved
1062 //type: 2 -- mobile confirmation received
1063 void updateMobileTaskReport(struct task_pool * t_pool, int task_no, int type, int w){
1064    struct task_pool * p = t_pool;
1065    for(;p!=NULL; p=p->next){
1066       if(p->m_task_report->task_id == task_no){
1067          if(type == 1){
1068             p->m_task_report->task_status = 3;
1069             p->m_task_report->m_dep_time[p->m_task_report->mobilities] = MPI_Wtime();
1070       break;
1071          }else if(type == 2){
```

```
1072            p->m_task_report->task_status = 1;
1073            p->m_task_report->m_arr_time[p->m_task_report->mobilities] = MPI_Wtime();
1074            p->m_task_report->mobilities++;
1075            p->m_task_report->task_worker = w;
1076          }
1077       }
1078    }
1079 }
1080
1081 struct worker_local_load * addWorkerLocalLoad(
1082                  struct worker_local_load * wlLoad,
1083                  float t_per, float t_sec, float t_load_avg,
1084                  int t_est_load_avg, long double t_cpu_uti, int t_run_proc){
1085    if(wlLoad == 0){
1086       wlLoad = (struct worker_local_load *)malloc(sizeof(struct worker_local_load));
1087       wlLoad->per = t_per;
1088       wlLoad->sec = t_sec;
1089       wlLoad->load_avg = t_load_avg;
1090       wlLoad->est_load_avg = t_est_load_avg;
1091       wlLoad->w_cpu_uti = t_cpu_uti;
1092       wlLoad->w_running_procs = t_run_proc;
1093       wlLoad->next = NULL;
1094    }else{
1095       struct worker_local_load * pl = wlLoad;
1096       while(pl->next != NULL)
1097       pl = pl->next;
1098       pl->next = (struct worker_local_load *)malloc(sizeof(struct worker_local_load));
1099       pl->next->per = t_per;
1100       pl->next->sec = t_sec;
1101       pl->next->load_avg = t_load_avg;
1102       pl->next->est_load_avg = t_est_load_avg;
1103       pl->next->w_cpu_uti = t_cpu_uti;
1104       pl->next->w_running_procs = t_run_proc;
1105       pl->next->next = 0;
1106    }
1107    return wlLoad;
1108 }
1109
1110 void recordLocalR(struct worker_task * w_ts, float P, int cores, double t_cpu_uti, int
       t_run_proc){
1111    struct worker_task * p = w_ts->next;
1112    while(p != NULL){
1113       if(!p->m_task->done && p->move_status != 1){
1114          if(p->local_R == 0)
1115             p->local_R = getActualRelativePower(P, t_cpu_uti, 0, t_run_proc, cores, 0, rank);
1116          else
1117             p->local_R = (p->local_R + getActualRelativePower(P, t_cpu_uti, 0, t_run_proc, cores
       , 0, rank))/2;
1118       }
1119       p = p->next;
1120    }
1121 }
1122
1123 void recordLocalLoad(struct worker_task * w_ts, float t_load_avg,
1124            int t_est_load_avg, long double t_cpu_uti, int t_run_proc){
1125    struct worker_task * p = w_ts->next;
1126    float t_per = 0;
1127    float t_sec = 0;
1128    while(p != NULL){
1129       if(!p->m_task->done && p->move_status != 1){
1130          int i = p->m_task->counter;
1131          t_per = ((i * 100) / (float)p->m_task->counter_max);
1132          t_sec = MPI_Wtime() - p->w_task_start;
```

```
1133            p->w_l_load = addWorkerLocalLoad(p->w_l_load, t_per, t_sec, t_load_avg, t_est_load_avg,
                t_cpu_uti, t_run_proc);
1134        }
1135        p = p->next;
1136    }
1137 }
1138
1139 float* getEstimatedExecutionTime(struct worker_load_task * w_l_t, int n, struct worker_task * p
        , int * dest_nps, struct estimated_cost * e_c, int cur_tasks){
1140    struct  worker_load w_local_loads = w_l_t->w_local_loads;
1141    int i = p->m_task->counter;
1142    //The work done before
1143    float Wd_before = p->m_task->m_work_start[p->m_task->moves-1];
1144    float Wd = ((i * 100) / (float)p->m_task->counter_max) - p->m_task->m_work_start[p->m_task->
          moves-1];
1145    //The time spent here to process the work done
1146    float Te = MPI_Wtime() - p->w_task_start;
1147    //the work left
1148    float Wl = 100 - Wd - Wd_before;
1149    //Total machine power(P=speed*cores)
1150    float P = w_local_loads.w_cpu_speed;
1151    //Number of cores for this machine
1152    int cores = w_local_loads.w_cores;
1153    float CPU_UTI = w_local_loads.w_cpu_uti_2;
1154    int ESTIMATED_LOAD_AVG = w_local_loads.estimated_load;
1155    int RUNNING_PROCESSES = w_local_loads.w_running_procs;
1156    float Rhn = getActualRelativePower(P, CPU_UTI, ESTIMATED_LOAD_AVG, RUNNING_PROCESSES, cores,
          *(dest_nps + rank -1), rank);
1157    float Rhe = p->local_R;
1158    float Th = (Wl * Rhe * Te)/(Wd * Rhn);
1159    //n: number of workers
1160    //T: Array of all estimated execution times
1161    float *T = (float *)malloc(sizeof(float) * n);
1162    struct worker_load * w_loads = w_l_t->w_loads;
1163    int i_T = 0;
1164    float Tn;
1165    for(; i_T < n; i_T++){
1166       if(i_T == rank-1)
1167       T[i_T] = Th;
1168       else{
1169          float remote_power = (w_loads + i_T)->w_cpu_speed;
1170          float remote_cpu_uti = (w_loads + i_T)->w_cpu_uti_2;
1171          int remote_ext_load_avg = (w_loads + i_T)->estimated_load;
1172          int remote_running_procs = (w_loads + i_T)->w_running_procs;
1173          int remote_cores = (w_loads + i_T)->w_cores;
1174          float Rnn = getActualRelativePower(remote_power, remote_cpu_uti, remote_ext_load_avg,
          remote_running_procs + 1, remote_cores, *(dest_nps + i_T), (w_loads + i_T)->w_rank);
1175          Tn = (Wl * Rhe * Te)/(Wd * Rnn);
1176          T[i_T] = Tn;
1177       }
1178    }
1179    e_c->task_no = p->m_task->m_task_id;
1180    e_c->cur_EC = Th;
1181    e_c->spent_here = Te;
1182    int i_t = 0, i_w = 0;
1183    for(i_t = 0; i_t < cur_tasks-1; i_t++){
1184       float Rhn = getActualRelativePower(P, CPU_UTI, ESTIMATED_LOAD_AVG, RUNNING_PROCESSES,
          cores, (i_t*-1)-1, rank);
1185       float Th = (Wl * Rhe * Te)/(Wd * Rhn);
1186       if((Wd * Rhn) != 0)
1187          e_c->cur_EC_after[i_t] = Th;
1188       else
1189          e_c->cur_EC_after[i_t] = 0;
```

```
1190    }
1191    for(i_T = 0; i_T < n; i_T++){
1192        if(i_T != rank-1 && (w_loads + i_T)->locked == 0){
1193            (e_c->other_ECs + i_w)->w_no = i_T;
1194            (e_c->other_ECs + i_w)->move_cost = getPredictedMoveTime(p->m_task, w_l_t, i_T + 1);
1195            float remote_power = (w_loads + i_T)->w_cpu_speed;
1196            float remote_cpu_uti = (w_loads + i_T)->w_cpu_uti_2;
1197            int remote_ext_load_avg = (w_loads + i_T)->estimated_load;
1198            int remote_running_procs = (w_loads + i_T)->w_running_procs;
1199            int remote_cores = (w_loads + i_T)->w_cores;
1200            //All Estimated costs for all workers
1201            for(i_t = 0; i_t < cur_tasks; i_t++){
1202                float Rnn = getActualRelativePower(remote_power, remote_cpu_uti, remote_ext_load_avg
        , remote_running_procs, remote_cores, (i_t + 1), (w_loads + i_T)->w_rank);
1203                if((Wd * Rnn) != 0)
1204                    Tn = (Wl * Rhe * Te)/(Wd * Rnn);
1205                else
1206                    Tn = 0;
1207                (e_c->other_ECs + i_w)->costs[i_t] = Tn;
1208            }
1209            i_w++;
1210        }
1211    }
1212    return T;
1213 }
1214
1215 void printEstimationCost(struct estimated_cost * e_c, int cur_tasks, int other_worker_count){
1216    int i_t = 0, i_t2 = 0, i_w = 0;
1217    printf("************************************************\n");
1218    printf("********  ESTIMATION COST FOR %d ***************\n", rank);
1219    printf("************************************************\n");
1220    for(i_t=0; i_t<cur_tasks; i_t++){
1221        printf("task: %d , EC: %.3f, Spent Here: %.3f\n", (e_c + i_t)->task_no, (e_c + i_t)->
      cur_EC, (e_c + i_t)->spent_here);
1222        printf("\tEC HERE: ");
1223        for(i_t2=0; i_t2<cur_tasks-1; i_t2++)
1224            printf("%10.3f", (e_c + i_t)->cur_EC_after[i_t2]);
1225        printf("\n");
1226        for(i_w=0; i_w<other_worker_count; i_w++){
1227            printf("\tECs @ %d :", (((e_c + i_t)->other_ECs + i_w)->w_no));
1228            for(i_t2=0; i_t2<cur_tasks; i_t2++)
1229                printf("%10.3f", (((e_c + i_t)->other_ECs + i_w)->costs[i_t2]));
1230            printf(" [Move Cost: %.4f]", ((e_c + i_t)->other_ECs + i_w)->move_cost);
1231            printf("\n");
1232        }
1233        printf("\tNew Allocation: w: %d, EC: %.3f\n", (e_c + i_t)->to_w, (e_c + i_t)->to_EC);
1234    }
1235    printf("\n************************************************\n\n");
1236 }
1237 //find the best mappin fot tasks based on the estimated costs
1238 void findBestTaskMapping(struct estimated_cost * e_c, int cur_tasks, int w_count){
1239    int * task_mapping = (int*)malloc(sizeof(int)*(w_count));
1240    int i=0, i_t=0, i_new_w=0;
1241    //initialize task mapping
1242    for(i=0; i<w_count+1; i++)
1243        task_mapping[i]=0;
1244    task_mapping[rank-1] = cur_tasks;
1245    //initialize the task allocation
1246    for(i_t=0; i_t<cur_tasks; i_t++){
1247        (e_c + i_t)->to_w = rank -1;
1248        (e_c + i_t)->to_EC = (e_c + i_t)->cur_EC;
1249        //Add the move cost
1250        for(i=0; i<w_count; i++)
```

```
1251            for(i_new_w=0; i_new_w<cur_tasks; i_new_w++)
1252                ((e_c + i_t)->other_ECs+i)->costs[i_new_w] = ((e_c + i_t)->other_ECs+i)->costs[
        i_new_w] + ((e_c + i_t)->other_ECs+i)->move_cost;
1253        }
1254        int trial = 0, improved = 1;
1255        do{
1256            //Find the slowest task;
1257            int s_t = -1;
1258            float s_ec = -1;
1259            //To select the first task which is the slowst
1260            for(i_t=0; i_t<cur_tasks; i_t++){
1261                //to garantee that the current task has spent over than 2 sec for having good
        estimation cost
1262                if((e_c + i_t)->spent_here > 2){
1263                    s_t = (e_c + i_t)->task_no;
1264                    s_ec = (e_c + i_t)->to_EC;
1265                    break;
1266                }
1267            }
1268            //break if there is no task whose spent time here noe exceed 2 sec
1269            if(s_t == -1) break;
1270            for(i_t=0; i_t<cur_tasks; i_t++){
1271                if((e_c + i_t)->spent_here > 2){
1272                    if((e_c + i_t)->to_EC > s_ec){
1273                        s_ec = (e_c + i_t)->to_EC;
1274                        s_t = (e_c + i_t)->task_no;
1275                    }
1276                }
1277            }
1278            //Find the best new location for the slowest task
1279            for(i_t=0; i_t<cur_tasks; i_t++){
1280                if((e_c + i_t)->task_no == s_t){
1281                    int new_w = (e_c + i_t)->to_w;
1282                    float new_EC = s_ec;
1283                    for(i=0; i<w_count; i++){
1284                        int w = ((e_c + i_t)->other_ECs + i)->w_no;
1285                        if (((e_c + i_t)->other_ECs + i)->costs[task_mapping[w]] < new_EC){
1286                            new_EC = ((e_c + i_t)->other_ECs + i)->costs[task_mapping[w]];
1287                            new_w = w;
1288                        }
1289                    }
1290                    if(new_w != (e_c + i_t)->to_w){
1291                        (e_c + i_t)->to_w = new_w;
1292                        (e_c + i_t)->to_EC = new_EC;
1293                        //change the mapping depending on the new findings
1294                        task_mapping[rank-1] = task_mapping[rank-1] - 1;
1295                        task_mapping[(e_c + i_t)->to_w] = task_mapping[(e_c + i_t)->to_w] + 1;
1296                    }else
1297                        improved = 0;
1298                    break;
1299
1300                }
1301            }
1302            if(improved == 1){
1303                //Update the task allocation details depending on the new findings
1304                for(i_t=0; i_t<cur_tasks; i_t++){
1305                    if((e_c + i_t)->spent_here > 2)
1306                        if((e_c + i_t)->task_no != s_t){
1307                            if((e_c + i_t)->to_w == rank -1)
1308                                (e_c + i_t)->to_EC = (e_c + i_t)->cur_EC_after[cur_tasks - task_mapping[(
        e_c + i_t)->to_w] - 1];
1309                            else{
1310                                int i_new_ec = 0;
```

```
1311                        for(i_new_ec=0; i_new_ec<w_count; i_new_ec++)
1312                            if(((e_c + i_t)->other_ECs + i_new_ec)->w_no == task_mapping[(e_c + i_t)
    ->to_w])
1313                                (e_c + i_t)->to_EC = ((e_c + i_t)->other_ECs + i_new_ec)->costs[
    task_mapping[(e_c + i_t)->to_w] - 1];
1314                    }
1315                }
1316            }
1317        }
1318        trial++;
1319    }while(improved == 1);
1320 }
1321
1322 void *worker_estimator(void * arg){
1323    double estimator_mid = 0;
1324    struct worker_load_task * w_l_t = (struct worker_load_task *)(arg);
1325    struct worker_task * p;
1326    int cur_tasks=0;
1327    #ifdef SYS_gettid
1328    pid_t tid = syscall(SYS_gettid);
1329    #else
1330    #error "SYS_gettid unavailable on this system"
1331    #endif
1332    w_l_t->estimator_tid = tid;
1333    struct worker_move_report * w_m_report = w_l_t->move_report;
1334    estimator_mid = MPI_Wtime();
1335    int i_d = 0;
1336    p = w_l_t->w_tasks->next;
1337    cur_tasks = 0;
1338    while(p != NULL){
1339        if(!p->m_task->done && (p->move_status != 1))
1340            cur_tasks++;
1341        p = p->next;
1342    }
1343    p = w_l_t->w_tasks->next;
1344    if(cur_tasks > 0){
1345        //new wights after changing the task mapping
1346        int * dest_nps = (int*)malloc(sizeof(int)*(numprocs-1));
1347        for(i_d=0; i_d<numprocs-1; i_d++)
1348            *(dest_nps + i_d) = 0;
1349        //init the estimation report
1350        int i_t = 0, i_w = 0;
1351        int other_worker_count = 0;
1352        for(i_w=0; i_w<numprocs-1; i_w++){
1353            if(i_w != rank-1)
1354                if((w_l_t->w_loads + i_w)->locked == 0)
1355                    other_worker_count++;
1356        }
1357        struct estimated_cost * e_c = (struct estimated_cost *)malloc(sizeof(struct estimated_cost
    ) * cur_tasks);
1358        for(i_t=0; i_t<cur_tasks; i_t++){
1359            (e_c + i_t)->cur_EC_after = (float*) malloc(sizeof(float) * (cur_tasks - 1));
1360            (e_c + i_t)->other_ECs = (struct other_estimated_costs*) malloc(sizeof(struct
    other_estimated_costs) * other_worker_count);
1361            for(i_w=0; i_w<other_worker_count; i_w++){
1362                ((e_c + i_t)->other_ECs + i_w)->costs = (float *) malloc(sizeof(float) * cur_tasks);
1363            }
1364        }
1365        i_t = 0;
1366        int report_done = 0;
1367        do{
1368            p = w_l_t->w_tasks->next;
1369            i_t = 0;
```

```
1370            while(p != NULL){
1371                if(!p->m_task->done && (p->move_status != 1)){
1372                    if(p->estimating_move == NULL){
1373                        //get the estimated execution time for this task
1374                        float * T = getEstimatedExecutionTime(w_l_t, numprocs-1, p, dest_nps, (e_c + (
    i_t++)), cur_tasks);
1375                        //Set the estimation costs on all other worker for this task
1376                        p->estimating_move = (struct estimation *)malloc(sizeof(struct estimation));
1377                        p->estimating_move->estimation_costs = T;
1378                        p->estimating_move->done = 0;
1379                        p->estimating_move->chosen_dest = -1;
1380                        p->estimating_move->gain_perc = 0;
1381                        p->estimating_move->on_dest_recalc = -1;
1382                    }else{
1383                        if(p->estimating_move->done != 1){
1384                            //get the estimated execution time for this task
1385                            float * T = getEstimatedExecutionTime(w_l_t, numprocs-1, p, dest_nps, (e_c
    + (i_t++)), cur_tasks);
1386                            //Set the estimation costs on all other worker for this task
1387                            p->estimating_move = (struct estimation *)malloc(sizeof(struct estimation))
    ;
1388                            p->estimating_move->estimation_costs = T;
1389                            p->estimating_move->done = 0;
1390                            p->estimating_move->chosen_dest = -1;
1391                            p->estimating_move->gain_perc = 0;
1392                            p->estimating_move->on_dest_recalc = -1;
1393                        }
1394                    }
1395                }
1396                p = p->next;
1397            }
1398            estimator_mid = MPI_Wtime();
1399            findBestTaskMapping(e_c, cur_tasks, other_worker_count);
1400            estimator_mid = MPI_Wtime();
1401            //Init move report
1402            int i_r = 0;
1403            for(i_r=0; i_r<numprocs-1; i_r++){
1404                (w_m_report + i_r)->w_id = i_r;
1405                (w_m_report + i_r)->num_of_tasks = 0;
1406                (w_m_report + i_r)->list_of_tasks = (int *)malloc(sizeof(int)*cur_tasks);
1407            }
1408            for(i_t=0; i_t<cur_tasks; i_t++){
1409                for(i_r=0; i_r<numprocs-1; i_r++){
1410                    if((w_m_report + i_r)->w_id == (e_c + i_t)->to_w){
1411                        (w_m_report + i_r)->list_of_tasks[(w_m_report + i_r)->num_of_tasks] = (e_c +
    i_t)->task_no;
1412                        (w_m_report + i_r)->num_of_tasks = (w_m_report + i_r)->num_of_tasks + 1;
1413                    }
1414                }
1415            }
1416            report_done = 1;
1417          }while(report_done == 0);
1418          //create move report
1419          p = w_l_t->w_tasks->next;
1420          while(p != NULL){
1421            if(!p->m_task->done && (p->move_status != 1))
1422                p->estimating_move = NULL;
1423                p = p->next;
1424            }
1425          }
1426          if(cur_tasks > 0)
1427            sendMoveReportToWorkers(w_l_t->move_report, w_l_t->w_loads);
1428        return NULL;
```

```
1429 }
1430
1431 void *worker_status(void *arg){
1432    struct worker_load_task * w_l_t = (struct worker_load_task *)(arg);
1433    //Get the thread number (Thread/Process ID)
1434    #ifdef SYS_gettid
1435    pid_t tid = syscall(SYS_gettid);
1436    #else
1437    #error "SYS_gettid unavailable on this system"
1438    #endif
1439    w_l_t->status_tid = tid;
1440    struct worker_load * local_load = (struct worker_load *)malloc(sizeof(struct worker_load));
1441    float load_avg = getLoad(), prev_load_avg;
1442    int w_cores = getNumberOfCores();
1443    float cpu_freq = getCoresFreq();
1444    local_load->w_rank = rank;
1445    strcpy(local_load->w_name, processor_name);
1446    local_load->m_id = 0;
1447    local_load->current_tasks = 0;
1448    local_load->total_task = 0;
1449    local_load->status = 0;
1450    local_load->w_cores = w_cores;
1451    local_load->w_cache_size = 0;
1452    local_load->w_cpu_speed = cpu_freq;
1453    local_load->w_load_avg_1 = load_avg;
1454    local_load->w_load_avg_2 = load_avg;
1455    local_load->locked = 0;
1456    local_load->estimated_load = 0;
1457    local_load->w_cpu_uti_2 = 0;
1458
1459    int state_worker = getProcessState(w_l_t->worker_tid, 0, 0);
1460    int state_estimator = getProcessState(w_l_t->worker_tid, 1, w_l_t->estimator_tid);
1461    local_load->w_running_procs = getRunningProc();
1462
1463    local_load->w_running_procs = local_load->w_running_procs - state_worker - state_estimator -
       1;
1464    if(local_load->w_running_procs < 0)
1465       local_load->w_running_procs = 0;
1466
1467    long double * a = (long double *)malloc(sizeof(long double) * 5);
1468    long double * b = (long double *)malloc(sizeof(long double) * 5);
1469
1470    getCPUValues(b);
1471    long double per = 0;
1472    int rp;
1473    local_load->w_cpu_uti_1 = per;
1474    local_load->w_cpu_uti_2 = per;
1475    w_l_t->w_local_loads = *local_load;
1476    sendInitialWorkerLoad(local_load, 0);
1477    prev_load_avg = load_avg;
1478    recordLocalR(w_tasks, cpu_freq, w_cores, per, local_load->w_running_procs);
1479    int load_info_size = sizeof(int) + sizeof(int) + sizeof(float) + sizeof(long double);
1480    int int_size = sizeof(int);
1481    int float_size = sizeof(float);
1482    int est_load = -1;
1483    void * d = (void*)malloc(load_info_size);
1484    struct worker_task * p;
1485    int cur_tasks=0;
1486    long double per_1 = per;
1487    long double per_2 = per;
1488    long double per_3 = per;
1489    float POWER_BASE = cpu_freq / w_cores;
1490    float POWER_LIMIT = 95.0;
```

```
1491    float cur_arp = -1;
1492    float arp_1 = -1;
1493    float arp_2 = -1;
1494    while(1){
1495       prev_load_avg = load_avg;
1496       //Obtaining the local load
1497       setLocalLoadInfo(a, b, &per, &rp, &load_avg);
1498       if(w_l_t){
1499          w_l_t->w_local_loads.w_load_avg_1 = prev_load_avg;
1500          w_l_t->w_local_loads.w_load_avg_2 = load_avg;
1501          w_l_t->w_local_loads.estimated_load = est_load;
1502          w_l_t->w_local_loads.w_running_procs = rp;
1503          w_l_t->w_local_loads.w_cpu_uti_1 = w_l_t->w_loads[rank-1].w_cpu_uti_2;
1504          w_l_t->w_local_loads.w_cpu_uti_2 = per;
1505       }
1506
1507       per_3 = per_2;
1508       per_2 = per_1;
1509       per_1 = per;
1510
1511       *((int*)d) = rp;
1512       *((int*)(d + int_size)) = est_load;
1513       *((float*)(d + 2 * int_size)) = load_avg;
1514       *((long double*)(d + 2 * int_size + float_size)) = per;
1515
1516       recordLocalR(w_tasks, cpu_freq, w_cores, per, rp);
1517
1518       //Get the cuurent running tasks
1519       p = w_l_t->w_tasks->next;
1520       cur_tasks = 0;
1521       while(p != NULL){
1522          if(!p->m_task->done && (p->move_status != 1))
1523             cur_tasks++;
1524          p = p->next;
1525       }
1526       if(cur_tasks > 0){
1527          cur_arp = getActualRelativePower(cpu_freq, per, est_load, rp, w_cores, 0, rank);
1528          if((cur_arp * 100 / POWER_BASE) < POWER_LIMIT){
1529             if(arp_1 == -1){
1530                arp_1 = cur_arp;
1531             }else{
1532                if(arp_2 == -1){
1533                   arp_2 = cur_arp;
1534                }else{
1535                   //TRIGGER
1536                   obtainLatestLoad(0);
1537                   arp_1 = -1;
1538                   arp_2 = -1;
1539                }
1540             }
1541          }else{
1542             arp_1 = -1;
1543             arp_2 = -1;
1544          }
1545       }
1546    }
1547 }
1548 ///Send get initial load request
1549 void notifyMaster(int t_id, int target_w, int master){
1550    int send_code = MOBILITY_NOTIFICATION_FROM_WORKER;
1551    int * data = (int*)malloc(sizeof(int)*2);
1552    *data = t_id;
1553    *(data + 1) = target_w;
```

```
1554    MPI_Send(&send_code, 1, MPI_INT, master, send_code, MPI_COMM_WORLD);
1555    MPI_Send(data, 2, MPI_INT, master, send_code, MPI_COMM_WORLD);
1556 }
1557
1558 void * move_mobile_task(void * arg){
1559    struct worker_task * w_t = (struct worker_task *)arg;
1560    while(w_t->go_move == 0) usleep(1);
1561    w_t->m_task->m_end_time[w_t->m_task->moves-1] = MPI_Wtime();
1562    pthread_mutex_lock( &mutex_w_sending );
1563    notifyMaster(w_t->task_id, w_t->go_to, 0);
1564    moving_task = 1;
1565    sendMobileTask(w_t->m_task, w_t->go_to, W_TO_W);
1566    moving_task = 0;
1567    pthread_mutex_unlock( &mutex_w_sending );
1568    return NULL;
1569 }
1570 ///Send get initial load request
1571 void sendInitialWorkerLoadRequest(int proc){
1572    int send_code = LOAD_REQUEST_FROM_MASTER;
1573    MPI_Ssend(&send_code, 1, MPI_INT, proc, send_code, MPI_COMM_WORLD);
1574 }
1575
1576 //type: 0 -> send task
1577 //type: 1 -> recv task
1578 void modifyWorkerLoadReportM(struct worker_load * report, int source, int target){
1579    report[source-1].current_tasks--;
1580    report[source-1].m_id++;
1581    report[source-1].status = 1;
1582    if(report[source-1].current_tasks == 0)
1583       report[source-1].status = 0;
1584    report[target-1].current_tasks++;
1585    report[target-1].m_id++;
1586    report[target-1].status = 1;
1587 }
1588
1589 //type: 0 -> send task
1590 //type: 1 -> recv task
1591 void modifyWorkerLoadReport(int w, struct worker_load * report, int n, int type){
1592    if(type == 0){
1593       report[w-1].current_tasks++;
1594       report[w-1].status = 1;
1595    }else if(type == 1){
1596       report[w-1].current_tasks--;
1597       report[w-1].total_task++;
1598       if(report[w-1].current_tasks == 0)
1599          report[w-1].status = 0;
1600    }
1601 }
1602
1603 //send ping message to the selected worker
1604 void getInitNetworkLatency(struct worker_load * w_report){
1605    double ping_value = sendPing(w_report->w_name);
1606    if(ping_value != 0.0)
1607       w_report->net_times.init_net_time = ping_value;
1608 }
1609
1610 void getInitialWorkerLoad(struct worker_load * report, int n){
1611    int i=0;
1612    for( i=1; i<n; i++)
1613       sendInitialWorkerLoadRequest(i);
1614    int msg_code = -1;
1615    int w = 0;
1616    for(i=1; i<n; i++){
```

```
1617        MPI_Recv(&msg_code, 1, MPI_INT, MPI_ANY_SOURCE, MPI_ANY_TAG, MPI_COMM_WORLD, &status);
1618        w = status.MPI_SOURCE;
1619        if(msg_code == 1){
1620            MPI_Recv(&report[w-1], sizeof(struct worker_load), MPI_CHAR, w, MPI_ANY_TAG,
        MPI_COMM_WORLD, &status);
1621            getInitNetworkLatency(&report[w-1]);
1622        }
1623    }
1624    printWorkerLoadReport(report, n);
1625 }
1626
1627 void setWorkerLoad(struct worker_load * report, int n, int source, int tag){
1628    int load_info_size = 0;
1629    MPI_Recv(&load_info_size, 1, MPI_INT, source, tag, MPI_COMM_WORLD, &status);
1630    void * load_info = (void *)malloc(load_info_size);
1631    MPI_Recv(load_info, load_info_size, MPI_CHAR, source, tag, MPI_COMM_WORLD, &status);
1632    report[source-1].m_id++;
1633    report[source-1].w_load_avg_1 = report[source-1].w_load_avg_2;
1634    report[source-1].w_load_avg_2 = *((float *)(load_info + 2 * sizeof(int)));
1635    report[source-1].estimated_load = *((int *)(load_info + sizeof(int)));
1636    report[source-1].w_cpu_uti_1 = report[source-1].w_cpu_uti_2;
1637    report[source-1].w_cpu_uti_2 = *((long double *)(load_info + 2 * sizeof(int) + sizeof(float))
        );
1638    report[source-1].w_running_procs = *((int *)load_info);
1639 }
1640
1641 void circulateWorkerLoadReportInitial(struct worker_load * report, int n){
1642    int i = 1;
1643    int send_code = UPDATE_LOAD_REPORT_REQUEST;
1644    int report_size = sizeof(struct worker_load)*(n-1);
1645    while(*(masterReceiving + (i) - 1) == 1) usleep(1);
1646    *(masterSending + i - 1) = 1;
1647    double load_agent_t1;
1648    load_agent_t1 = MPI_Wtime();
1649    double new_net_lat = MPI_Wtime();
1650    MPI_Ssend(&send_code, 1, MPI_INT, i, send_code, MPI_COMM_WORLD);
1651    new_net_lat = MPI_Wtime() - new_net_lat;
1652    MPI_Send(&report_size, 1, MPI_INT, i, send_code, MPI_COMM_WORLD);
1653    MPI_Send(report, report_size, MPI_CHAR, i, send_code, MPI_COMM_WORLD);
1654    *(masterSending + i - 1) = 0;
1655 }
1656
1657 void sendLatestLoad(struct worker_load * report, int n, int worker){
1658    int i = worker;
1659    int send_code = LOAD_INFO_FROM_MASTER;
1660    int report_size = sizeof(struct worker_load)*(n-1);
1661    while(*(masterReceiving + (i) - 1) == 1) usleep(1);
1662    *(masterSending + i - 1) = 1;
1663    MPI_Send(&send_code, 1, MPI_INT, i, send_code, MPI_COMM_WORLD);
1664    MPI_Send(&report_size, 1, MPI_INT, i, send_code, MPI_COMM_WORLD);
1665    MPI_Send(report, report_size, MPI_CHAR, i, send_code, MPI_COMM_WORLD);
1666    *(masterSending + i - 1) = 0;
1667 }
1668
1669 void circulateWorkerLoadReport(struct worker_load * report, int to_worker, int n){
1670    int i = to_worker;
1671    int send_code = UPDATE_LOAD_REPORT_REQUEST;
1672    int report_size = sizeof(struct worker_load)*(n-1);
1673    pthread_mutex_lock( &mutex_load_circulating );
1674    MPI_Send(&send_code, 1, MPI_INT, i, send_code, MPI_COMM_WORLD);
1675    MPI_Send(&report_size, 1, MPI_INT, i, send_code, MPI_COMM_WORLD);
1676    MPI_Send(report, report_size, MPI_CHAR, i, send_code, MPI_COMM_WORLD);
1677    pthread_mutex_unlock( &mutex_load_circulating );
```

```
1678 }
1679
1680 void recvWorkerLoadReport(struct worker_load * report, int source, int tag){
1681    int report_size = 0;
1682    MPI_Recv(&report_size, 1, MPI_INT, source, tag, MPI_COMM_WORLD, &status);
1683    MPI_Recv(report, report_size, MPI_CHAR, source, tag, MPI_COMM_WORLD, &status);
1684 }
1685
1686 int selectWorkerToCheckLatency(struct worker_load * report, int n){
1687    int w = -1;
1688    int i;
1689    for(i = 0; i < n; i++){
1690       if(report[i].status != 4){
1691          w = report[i].w_rank;
1692          break;
1693       }
1694    }
1695    return w;
1696 }
1697
1698 void* networkLatencyFun(void * arg){
1699    struct worker_load * w_load_report = (struct worker_load *)arg;
1700    double new_net_lat = 0;
1701    int w = -1;
1702    while(1){
1703       for(w=0;w<numprocs-1;w++){
1704          new_net_lat = sendPing(w_load_report[w].w_name);
1705          w_load_report[w].net_times.cur_net_time = new_net_lat;
1706       }
1707       printWorkerLoadReport(w_load_report, numprocs);
1708       sleep(3);
1709    }
1710 }
1711
1712 void* workerLoadReportFun(void * arg){
1713    struct worker_load * w_load_report = (struct worker_load *)arg;
1714    int i =0;
1715    while(1){
1716       sleep(1);
1717       double circ_start = MPI_Wtime();
1718       circulateWorkerLoadReportInitial(w_load_report, numprocs);
1719       if( i++ == 3)
1720          sendLatestLoad(w_load_report, numprocs, 1);
1721       double circ_end = MPI_Wtime();
1722       printf("[%d]. circ_time: %lf\n", rank, circ_end - circ_start);
1723   }
1724 }
1725
1726 ///send confirmation to worker for accepting receiving the result from the worker
1727 void sendRecvConfirmation(int w){
1728    int send_code = SENDING_CONFIRMATION_FROM_MASTER;
1729    MPI_Send(&send_code, 1, MPI_INT, w, send_code, MPI_COMM_WORLD);
1730 }
1731
1732 void sendMobileConfirmationToWorker(int w, int permitted_tasks){
1733    int send_code = MOBILITY_ACCEPTANCE_FROM_WORKER;
1734    //Send confirmation to the source worker
1735    MPI_Send(&send_code, 1, MPI_INT, w, send_code, MPI_COMM_WORLD);
1736    MPI_Send(&permitted_tasks, 1, MPI_INT, w, send_code, MPI_COMM_WORLD);
1737 }
1738
1739 void sendMobileConfirmation(int t_id, int source, int master){
1740    int send_code = MOBILITY_CONFIRMATION_FROM_WORKER;
```

```
1741    //Send confirmation to the master
1742    MPI_Send(&send_code, 1, MPI_INT, master, send_code, MPLCOMM_WORLD);
1743    int move_confirmation[2];
1744    move_confirmation[0] = source;
1745    move_confirmation[1] = t_id;
1746    MPI_Send(move_confirmation, 2, MPI_INT, master, send_code, MPLCOMM_WORLD);
1747    //Send Confirmation to the source worker
1748    MPI_Send(&send_code, 1, MPI_INT, source, send_code, MPLCOMM_WORLD);
1749    MPI_Send(&t_id, 1, MPI_INT, source, send_code, MPLCOMM_WORLD);
1750 }
1751
1752 void recvMobileConfirmationM(struct worker_load * report, struct task_pool * pool, int w, int
        msg_code){
1753    int move_confirmation[2];
1754    MPI_Recv(move_confirmation, 2, MPI_INT, w, msg_code, MPLCOMM_WORLD, &status);
1755    //Update the worker report.
1756    modifyWorkerLoadReportM(report, move_confirmation[0], w);
1757    //Update the task pool report
1758    updateMobileTaskReport(pool, move_confirmation[1], 2, move_confirmation[0]);
1759 }
1760
1761 void sendMultiMsgs(void *input, int dataLen, int limit, int proc, int tag, MPI_Datatype dataType
        ){
1762    int msgCount = (dataLen/limit);
1763    if((dataLen % limit) != 0) msgCount++;
1764    int msgSize;
1765    int i=0;
1766    MPI_Ssend(&msgCount, 1, MPI_INT, proc, tag, MPLCOMM_WORLD);
1767    for(i = 0; i<msgCount; i++){
1768       if(dataLen < limit)
1769          msgSize = dataLen;
1770       else
1771          msgSize = limit;
1772       MPI_Ssend(input + (i * limit), msgSize, dataType, proc, tag + i + 1, MPLCOMM_WORLD);
1773       dataLen = dataLen - msgSize;
1774    }
1775 }
1776
1777 void recvMultiMsgs(void * input, int dataLen, int limit, int source, MPI_Datatype dataType, int
        tag){
1778    int msgSize ;
1779    int msgCount;
1780    int i=0;
1781    MPI_Recv(&msgCount, 1 , MPI_INT, source, tag, MPLCOMM_WORLD, &status);
1782    for(i = 0; i<msgCount; i++){
1783       if(dataLen < limit)
1784          msgSize = dataLen;
1785       else
1786          msgSize = limit;
1787       MPI_Recv(input + (i * limit), msgSize, dataType, source, tag + i + 1, MPLCOMM_WORLD, &
        status);
1788       dataLen = dataLen - msgSize;
1789    }
1790 }
1791 //Send the shared data to a worker
1792 void sendSharedData(void *shared_data, int data_len, int w){
1793    if(data_len != 0){
1794       int send_code = SHARED_DATA_FROM_MASTER;
1795       MPI_Ssend(&send_code, 1, MPI_INT, w, send_code, MPLCOMM_WORLD);
1796       MPI_Ssend(&data_len, 1, MPI_INT, w, send_code, MPLCOMM_WORLD);
1797       sendMultiMsgs( shared_data, data_len, MSG_LIMIT, w, send_code, MPI_CHAR);
1798    }
1799 }
```

```
1800 //Send the shared data to all workers
1801 void sendSharedDataToAll(void *shared_data, int shared_data_size, int shared_data_len, int n){
1802    int i=0;
1803    for( i=1; i<n; i++)
1804       sendSharedData(shared_data, shared_data_size*shared_data_len, i);
1805 }
1806
1807 void initHWFarm(int argc, char ** argv){
1808    int provided;
1809    MPI_Init_thread(&argc, &argv, MPI_THREAD_MULTIPLE, &provided);
1810    MPI_Comm_size(MPI_COMM_WORLD, &numprocs);
1811    MPI_Comm_rank(MPI_COMM_WORLD, &rank);
1812    MPI_Get_processor_name(processor_name, &namelen);
1813    startTime = MPI_Wtime();
1814 }
1815
1816 void finalizeHWFarm(){
1817    MPI_Finalize();
1818 }
1819
1820 void hwfarm(fp worker,int tasks,
1821             void *input, int inSize,int inLen,
1822             void *shared_data, int shared_data_size, int shared_data_len,
1823             void *output, int outSize, int outLen, hwfarm_state main_state,
1824             int mobility){
1825
1826    MPI_Barrier(MPI_COMM_WORLD);
1827    //MASTER PROCESS
1828    if(rank == 0){
1829       start_time = MPI_Wtime();
1830       int m_cores = getNumberOfCores();
1831       if(m_cores == 0)
1832          m_cores = 1;
1833       Master_FREQ = getCoresFreq() / m_cores;
1834       int w=0, w_msg_code = 0, mR = 0, dest_w = -1, w_i = 0;
1835       if(isFirstCall){
1836          w_load_report = (struct worker_load *)malloc(sizeof(struct worker_load)* (numprocs - 1)
     );
1837          w_load_report_tmp = (struct worker_load *)malloc(sizeof(struct worker_load)* (numprocs
     - 1));
1838          getInitialWorkerLoad(w_load_report, numprocs);
1839       }
1840       struct task_pool * pool = 0;
1841       pool = create_task_pool(tasks, input, inLen, inSize,
1842                               output, outLen, outSize,
1843                               main_state.state_data, main_state.state_len,
1844                               main_state.counter, main_state.max_counter);
1845       masterReceiving = (int *)malloc((sizeof(int) * (numprocs - 1)));
1846       masterSending = (int *)malloc((sizeof(int) * (numprocs - 1)));
1847       for(mR = 0; mR < numprocs - 1; mR++){
1848          *(masterReceiving + mR) = 0;
1849          *(masterSending + mR) = 0;
1850       }
1851
1852       struct mobile_task_report * m_t_r;
1853       int processing_tasks = 0;
1854
1855       //Distributing tasks based on load on workers based on the allocation model
1856       int WORKERS_COUNT = numprocs - 1;
1857       int * tasksPerWorker = (int *)malloc(sizeof(int) * WORKERS_COUNT);
1858       int dis_tasks = tasks;
1859       for(w_i = 0; w_i < WORKERS_COUNT; w_i++)
1860          tasksPerWorker[w_i] = 0;
```

```
1861
1862        int C=0;//Total number of cores for all workers
1863        for(w_i = 0; w_i < WORKERS_COUNT; w_i++)
1864            C += w_load_report[w_i].w_cores;
1865        if(C > 0 && dis_tasks > 0){
1866            for(w_i = 0; w_i < WORKERS_COUNT; w_i++){
1867                int dis_task_i = ceil(w_load_report[w_i].w_cores * dis_tasks * 1.0 / C);
1868                tasksPerWorker[w_i] = dis_task_i;
1869                dis_tasks -= dis_task_i;
1870                C -= w_load_report[w_i].w_cores;
1871                if(dis_tasks <= 0) break;
1872            }
1873        }
1874        ///Send the shared data to the workers
1875        sendSharedDataToAll(shared_data, shared_data_size, shared_data_len, numprocs);
1876        ///Send the tasks to the workers
1877        while((m_t_r = getReadyTask(pool)) != NULL){
1878            ///Get the numbers of tasks allocated to each worker
1879            getValidWorker(tasksPerWorker, WORKERS_COUNT, &dest_w);
1880            if(dest_w == -1)
1881                break;
1882            ///Send the task to the selected worker 'dest_w'
1883            sendMobileTaskM(m_t_r, dest_w);
1884            ///Modify the status of the worker
1885            modifyWorkerLoadReport(dest_w, w_load_report, numprocs, 0);
1886            processing_tasks++;
1887        }
1888
1889        if(isFirstCall){
1890            pthread_create(&w_load_report_th, NULL, workerLoadReportFun, w_load_report);
1891            pthread_create(&w_network_latency_th, NULL, networkLatencyFun, w_load_report);
1892            isFirstCall = 0;
1893        }
1894
1895        do{
1896            ///Receive the msg code first; depending on this code,
1897            ///the type of data will be detected
1898            recvMsgCode(&w,&w_msg_code);
1899            ///Load comes from a worker
1900            if(w_msg_code == INIT_LOAD_FROM_WORKER){
1901                setWorkerLoad(w_load_report, numprocs, w, w_msg_code);
1902            }else if(w_msg_code == LATEST_LOAD_REQUEST){
1903                sendLatestLoad(w_load_report, numprocs, w);
1904            }else if(w_msg_code == UPDATE_LOAD_REPORT_REQUEST){
1905                recvWorkerLoadReport(w_load_report_tmp, w, w_msg_code);
1906                int i=0;
1907                for(i=0; i<numprocs-1; i++){
1908                    w_load_report[i].m_id = w_load_report_tmp[i].m_id;
1909                    w_load_report[i].w_load_avg_1 = w_load_report_tmp[i].w_load_avg_1;
1910                    w_load_report[i].w_load_avg_2 = w_load_report_tmp[i].w_load_avg_2;
1911                    w_load_report[i].estimated_load = w_load_report_tmp[i].estimated_load;
1912                    w_load_report[i].w_running_procs = w_load_report_tmp[i].w_running_procs;
1913                    w_load_report[i].w_cpu_uti_1 = w_load_report_tmp[i].w_cpu_uti_1;
1914                    w_load_report[i].w_cpu_uti_2 = w_load_report_tmp[i].w_cpu_uti_2;
1915                    w_load_report[i].locked = w_load_report_tmp[i].locked;
1916                }
1917
1918                printWorkerLoadReport(w_load_report, numprocs);
1919            }else if(w_msg_code == RESULTS_FROM_WORKER){
1920                *(masterReceiving + w - 1) = 1;
1921                while(*(masterSending + (w) - 1) == 1) usleep(1);
1922                ///Send confirmation to the worker 'w' to process
1923                sendRecvConfirmation(w);
```

```
1924            ///modify the load status for the sender;w: worker who
1925            ///finished executing the task
1926            modifyWorkerLoadReport(w, w_load_report, numprocs, 1);
1927            printWorkerLoadReport(w_load_report, numprocs);
1928            processing_tasks--;
1929            ///Receive the task results
1930            recvMobileTaskM(pool, w, w_msg_code);
1931            ///Unlock the receiving from that worker 'w'
1932            *(masterReceiving + w - 1) = 0;
1933            ///If there are tasks in the task pool
1934            if((m_t_r = getReadyTask(pool)) != NULL){
1935               dest_w = w;
1936               sendMobileTaskM(m_t_r, dest_w);
1937               modifyWorkerLoadReport(dest_w, w_load_report, numprocs, 0);
1938               printWorkerLoadReport(w_load_report, numprocs);
1939               processing_tasks++;
1940            }
1941
1942         }else if (w_msg_code == MOBILITY_CONFIRMATION_FROM_WORKER){
1943            ///Receive a confirmation from the workers who made the
1944            ///movements to modify the worker status
1945            recvMobileConfirmationM(w_load_report, pool, w, w_msg_code);
1946            printWorkerLoadReport(w_load_report, numprocs);
1947         }else if (w_msg_code == MOBILITY_NOTIFICATION_FROM_WORKER){
1948            ///Receive moving operation occurs now
1949            recvMovingNotification(w_load_report, numprocs, w, w_msg_code);
1950         }
1951      }while(processing_tasks > 0);
1952      terminateWorkers(numprocs);
1953      taskOutput(pool, output, outLen, outSize);
1954      free(pool);
1955      end_time = MPI_Wtime();
1956      printf("Total Time: %.5f\n", end_time - start_time);
1957
1958   }else{//WORKER PROCESS
1959      int w = 0, w_msg_code = 0;
1960      w_tasks = (struct worker_task*)malloc(sizeof(struct worker_task));
1961      w_tasks->task_id = -1;
1962      w_tasks->next = NULL;
1963      if(isFirstCall){
1964         workers_load_report = (struct worker_load *)malloc(sizeof(struct worker_load) * (
       numprocs-1));
1965         w_l_t = (struct worker_load_task *)malloc(sizeof(struct worker_load_task));
1966         w_l_t->w_loads = workers_load_report;
1967         w_l_t->move_report = (struct worker_move_report *)malloc(sizeof(struct
       worker_move_report)*(numprocs-1));
1968         isFirstCall = 0;
1969      }
1970      w_l_t->w_tasks = w_tasks;
1971      w_l_t->hold.on_hold = 0;
1972      w_l_t->hold.holded_on = 0;
1973      w_l_t->hold.holded_from = 0;
1974      w_l_t->hold.hold_time = 0;
1975      w_l_t->worker_tid = getpid();
1976      ///Pointer to the shared data which will be accebile amongst all tasks
1977      void *shared_data = NULL;
1978      int w_shared_totalsize = 0;
1979      do{
1980         ///Receive the message code from the master or from the
1981         ///source worker who wants to send the task to it.
1982         recvMsgCode(&w, &w_msg_code);
1983         ///Run the worker laod agent
1984         if(w_msg_code == LOAD_REQUEST_FROM_MASTER){
```

```
1985            pthread_create(&w_load_pth, NULL, worker_status, w_l_t);
1986        }else if(w_msg_code == TERMINATE_THE_WORKER){
1987            printf("[%d]. TERMINATE_THE_WORKER.\n", rank);
1988            break;
1989        }else if(w_msg_code == LOAD_INFO_FROM_MASTER){
1990            recvWorkerLoadReport(w_l_t->w_loads, w, w_msg_code);
1991            printWorkerLoadReport(w_l_t->w_loads, numprocs);
1992            if(mobility == 1)
1993                pthread_create(&w_estimator_pth, NULL, worker_estimator, w_l_t);
1994        }else if(w_msg_code == SENDING_CONFIRMATION_FROM_MASTER){
1995            worker_sending = 1;
1996        }else if(w_msg_code == MOBILITY_ACCEPTANCE_FROM_WORKER){
1997            int num_tasks = 0;
1998            MPI_Recv(&num_tasks, 1, MPI_INT, w, w_msg_code, MPI_COMM_WORLD, &status);
1999            if(num_tasks > 0){
2000                if(w_l_t->move_report != NULL){
2001                    int cur_num_of_tasks = (w_l_t->move_report + w - 1)->num_of_tasks;
2002                    int * cur_list_of_tasks = (w_l_t->move_report + w - 1)->list_of_tasks;
2003                    if(cur_num_of_tasks > 0 && cur_num_of_tasks >= num_tasks)
2004                        if(cur_list_of_tasks != NULL){
2005                            int i_tt = 0;
2006                            for(i_tt=0;i_tt<num_tasks; i_tt++){
2007                                printf("%d\n", *(cur_list_of_tasks + i_tt));
2008                                struct worker_task * wT = w_tasks->next;
2009                                for(;wT!=0;wT=wT->next){
2010                                    if((*(cur_list_of_tasks + i_tt) == wT->task_id) && (wT->
    move_status != 1)){
2011                                        wT->move = 1;
2012                                        wT->go_to = w;
2013                                        if(wT->moving_pth == 0)
2014                                            pthread_create(&wT->moving_pth, NULL, move_mobile_task, wT);
2015                                        break;
2016                                    }
2017                                }
2018                            }
2019                        }
2020                }
2021            }else{
2022                printWorkerLoadReport(w_l_t->w_loads, numprocs);
2023            }
2024        }else if(w_msg_code == UPDATE_LOAD_REPORT_REQUEST){
2025            recvWorkerLoadReport(w_l_t->w_loads, w, w_msg_code);
2026            w_l_t->w_loads[rank-1].m_id++;
2027            w_l_t->w_loads[rank-1].w_load_avg_1 = w_l_t->w_local_loads.w_load_avg_1;
2028            w_l_t->w_loads[rank-1].w_load_avg_2 = w_l_t->w_local_loads.w_load_avg_2;
2029            w_l_t->w_loads[rank-1].estimated_load = w_l_t->w_local_loads.estimated_load;
2030            w_l_t->w_loads[rank-1].w_running_procs = w_l_t->w_local_loads.w_running_procs;
2031            w_l_t->w_loads[rank-1].w_cpu_uti_1 = w_l_t->w_local_loads.w_cpu_uti_1;
2032            w_l_t->w_loads[rank-1].w_cpu_uti_2 = w_l_t->w_local_loads.w_cpu_uti_2;
2033            w_l_t->w_loads[rank-1].locked = w_l_t->w_local_loads.locked;
2034            if(rank+1 < numprocs)
2035                circulateWorkerLoadReport(workers_load_report, rank+1, numprocs);
2036            else
2037                circulateWorkerLoadReport(workers_load_report, 0, numprocs);
2038        }else if(w_msg_code == TASK_FROM_MASTER){
2039            double task_net_t = MPI_Wtime();
2040            struct worker_task * w_task = (struct worker_task*)malloc(sizeof(struct worker_task)
    );
2041            w_task->m_task = (struct mobile_task *)malloc(sizeof(struct mobile_task));
2042            w_task->m_task->move_stats.start_move_time = MPI_Wtime();
2043
2044            recvMobileTask(w_task->m_task, w, M_TO_W, w_msg_code);
2045
```

```
2046            w_task->m_task->move_stats.net_time = task_net_t - w_task->m_task->move_stats.
        start_move_time;
2047
2048            w_task->m_task->task_fun = worker;
2049            //Set Shared values
2050            if(shared_data != NULL){
2051               w_task->m_task->shared_data = shared_data;
2052               w_task->m_task->shared_data_length = w_shared_totalsize/shared_data_size;
2053               w_task->m_task->shared_data_item_size = shared_data_size;
2054            }
2055
2056            w_task->task_id = w_task->m_task->m_task_id;
2057            w_task->w_task_start = MPI_Wtime();
2058            w_task->w_l_load = NULL;
2059            w_task->move = 0;
2060            w_task->go_move = 0;
2061            w_task->go_to = 0;
2062            w_task->move_status = 0;
2063            w_task->estimating_move = NULL;
2064            w_task->moving_pth = 0;
2065            w_task->local_R = 0;
2066            w_tasks = newWorkerTask(w_tasks, w_task);
2067            pthread_create(&w_task->task_pth, NULL, workerMobileTask, w_task->m_task);
2068         }else if(w_msg_code == MOBILITY_REQUEST_FROM_WORKER){
2069            int*msg_numTasks_load_no = (int*)malloc(sizeof(int)*2);
2070            MPI_Recv(msg_numTasks_load_no, 2, MPI_INT, w, w_msg_code, MPI_COMM_WORLD, &status);
2071            printWorkerLoadReport(w_l_t->w_loads, numprocs);
2072            int num_task = *msg_numTasks_load_no;
2073            if(w_l_t->hold.on_hold == 0){
2074               w_l_t->hold.on_hold = 1;
2075               w_l_t->hold.holded_on = num_task;
2076               w_l_t->hold.holded_from = w;
2077               w_l_t->hold.hold_time = MPI_Wtime();
2078               w_l_t->w_local_loads.locked = 1;
2079               sendMobileConfirmationToWorker(w, num_task);
2080            }else{
2081               sleep(1);
2082               sendMobileConfirmationToWorker(w, 0);
2083            }
2084         }else if(w_msg_code == MOBILITY_CONFIRMATION_FROM_WORKER){
2085            int t_id = -1;
2086            MPI_Recv(&t_id, 1, MPI_INT, w, w_msg_code, MPI_COMM_WORLD, &status);
2087            w_l_t->w_loads[rank-1].m_id++;
2088            struct worker_task * wT = w_tasks->next;
2089            for(;wT!=0;wT=wT->next)
2090               if(t_id == wT->task_id)
2091                  if(wT->move == 1 && wT->go_move == 1 && wT->move_status == 0){
2092                     wT->move_status = 1;
2093                     break;
2094                  }
2095         }else if(w_msg_code == TASK_FROM_WORKER){
2096            struct worker_task * w_task = (struct worker_task*)malloc(sizeof(struct worker_task)
        );
2097            w_task->m_task = (struct mobile_task *)malloc(sizeof(struct mobile_task));
2098            recvMobileTask(w_task->m_task, w, W_TO_W, w_msg_code);
2099            w_task->m_task->task_fun = worker;
2100            w_task->m_task->shared_data = shared_data;
2101            w_task->task_id = w_task->m_task->m_task_id;
2102            w_task->w_task_start = MPI_Wtime();
2103            w_task->w_l_load = NULL;
2104            w_task->move = 0;
2105            w_task->go_move = 0;
2106            w_task->go_to = 0;
```

```
2107                w_task->move_status = 0;
2108                w_task->estimating_move = NULL;
2109                w_task->moving_pth = 0;
2110                w_task->local_R = 0;
2111                w_tasks = newWorkerTask(w_tasks, w_task);
2112                //Sending a confirmation to the source worker...
2113                sendMobileConfirmation(w_task->task_id, w, 0);
2114                //Update the load no on local
2115                w_l_t->w_loads[rank-1].m_id++;
2116                w_l_t->hold.holded_on--;
2117                if(w_l_t->hold.holded_on == 0){
2118                    w_l_t->hold.on_hold = 0;
2119                    w_l_t->hold.holded_on = 0;
2120                    w_l_t->hold.hold_time = 0;
2121                    w_l_t->w_local_loads.locked = 0;
2122                }
2123                pthread_create(&w_task->task_pth, NULL, workerMobileTask, w_task->m_task);
2124            }else if(w_msg_code == SHARED_DATA_FROM_MASTER){
2125                shared_data = recvSharedData(shared_data, &w_shared_totalsize, w, w_msg_code);
2126            }
2127        }while(w_msg_code != TERMINATE_THE_WORKER);
2128    }
2129    MPI_Barrier(MPI_COMM_WORLD);
2130 }
```

Listing B.2: The HWFarm Skeleton C source code

Bibliography

[1] Vmotion. VMware, inc. http://www.vmware.com/products/vcenter-server.

[2] Platform Computing, Inc. LSF 6.0 User's Guide., "2003. http://www-03.ibm.com/systems/services/platformcomputing/lsf.html".

[3] Recursion Software, Inc .2591 North Dallas Parkway, Suit 200, Frisco, TX 75034, Voyager User Guide, 2005. http://www.recursionsw.com.

[4] J. Abawajy. Autonomic Job Scheduling Policy for Grid Computing. In V. Sunderam, G. van Albada, P. Sloot, and J. Dongarra, editors, *Computational Science ICCS 2005*, volume 3516 of *Lecture Notes in Computer Science*, pages 213–220. Springer Berlin Heidelberg, 2005.

[5] A. Aggarwal, A. K. Chandra, and M. Snir. On Communication Latency in PRAM Computations. In *Proceedings of the First Annual ACM Symposium on Parallel Algorithms and Architectures*, SPAA '89, pages 11–21, New York, NY, USA, 1989. ACM.

[6] A. Aggarwal, A. K. Chandra, and M. Snir. Communication Complexity of PRAMs. *Theor. Comput. Sci.*, 71(1):3–28, Mar. 1990.

[7] A. D. I. Al Zain. *Implementing high-level parallelism on computational GRIDs.* PhD thesis, School of Mathematical and Computer Sciences, Heriot-Watt University, 2006.

[8] E. Alba, F. Almeida, M. Blesa, J. Cabeza, C. Cotta, M. Díaz, I. Dorta, J. Gabarró, C. León, J. Luna, et al. MALLBA: A library of skeletons for

combinatorial optimisation. In *Euro-Par 2002 Parallel Processing*, pages 927–932. Springer, 2002.

[9] M. Aldinucci, M. Danelutto, and P. Dazzi. Muskel: an expandable skeleton environment. *Scalable Computing: Practice and Experience*, 8(4), 2001.

[10] M. Aldinucci, M. Danelutto, and P. Kilpatrick. Skeletons for multi/many-core systems. In *Parallel Computing: From Multicores and GPU's to Petascale (Proc. of PARCO 2009, Lyon, France)*, pages 265–272, 2010.

[11] M. Aldinucci, M. Danelutto, P. Kilpatrick, M. Meneghin, and M. Torquati. Accelerating code on multi-cores with FastFlow. In *Euro-Par 2011 Parallel Processing*, pages 170–181. Springer, 2011.

[12] M. Aldinucci, M. Danelutto, and P. Teti. An advanced environment supporting structured parallel programming in Java. *Future Generation Computer Systems*, 19(5):611–626, 2003.

[13] A. Alexandrov, M. F. Ionescu, K. E. Schauser, and C. Scheiman. LogGP: Incorporating Long Messages into the LogP Model-One Step Closer Towards a Realistic Model for Parallel Computation. In *Proceedings of the Seventh Annual ACM Symposium on Parallel Algorithms and Architectures*, SPAA '95, pages 95–105, New York, NY, USA, 1995. ACM.

[14] M. Ålind, M. V. Eriksson, and C. W. Kessler. BlockLib: a skeleton library for Cell broadband engine. In *Proceedings of the 1st international workshop on Multicore software engineering*, pages 7–14. ACM, 2008.

[15] M. Alt and S. Gorlatch. A prototype grid system using Java and RMI. In *Parallel Computing Technologies*, pages 401–414. Springer, 2003.

[16] M. Alt and S. Gorlatch. Using skeletons in a Java-based grid system. In *Euro-Par 2003 Parallel Processing*, pages 742–749. Springer, 2003.

[17] S. F. Altschul, W. Gish, W. Miller, E. W. Myers, and D. J. Lipman. Basic local alignment search tool. *Journal of Molecular Biology*, 215(3):403–410, 1990.

[18] L. O. Andersen. *Program analysis and specialization for the C programming language*. PhD thesis, University of Cophenhagen, 1994.

[19] G. R. Andrews. *Foundations of Parallel and Distributed Programming*. Addison-Wesley Longman Publishing Co., Inc., Boston, MA, USA, 1st edition, 1999.

[20] J. N. Arabe, A. Beguelin, B. Lowekamp, E. Seligman, M. Starkey, and P. Stephan. Dome: Parallel Programming in a Heterogeneous Multi-User Environment. Technical report, Pittsburgh, PA, USA, 1995.

[21] K. A. Armih. *Toward Optimised Skeletons for Heterogeneous Parallel Architecture With Performance Cost Model*. PhD thesis, School of Mathematical and Computer Sciences, Heriot-Watt University, 2013.

[22] J. Arndt and C. Haenel. *Pi-unleashed*. Springer Science & Business Media, 2001.

[23] P. Au, J. Darlington, M. Ghanem, Y.-k. Guo, H. To, and J. Yang. Co-ordinating heterogeneous parallel computation. In L. Boug, P. Fraigniaud, A. Mignotte, and Y. Robert, editors, *Euro-Par'96 Parallel Processing*, volume 1123 of *Lecture Notes in Computer Science*, pages 601–614. Springer Berlin Heidelberg, 1996.

[24] B. Bacci, M. Danelutto, S. Pelagatti, and M. Vanneschi. SkIE: a heterogeneous environment for HPC applications. *Parallel Computing*, 25(13):1827–1852, 1999.

[25] A. Barak, S. Guday, and R. G. Wheeler. *The MOSIX Distributed Operating System: Load Balancing for UNIX*. Springer-Verlag New York, Inc., Secaucus, NJ, USA, 1993.

[26] P. Barham, B. Dragovic, K. Fraser, S. Hand, T. Harris, A. Ho, R. Neugebauer, I. Pratt, and A. Warfield. Xen and the art of virtualization. In *ACM SIGOPS Operating Systems Review*, volume 37, pages 164–177. ACM, 2003.

[27] A. Beguelin, J. Dongarra, A. Geist, R. Manchek, and V. Sunderam. A User's Guide to PVM Parallel Virtual Machine. Technical report, Knoxville, TN, USA, 1991.

[28] E. Belloni and C. Marcos. Modeling of mobile-agent applications with UML. In *Proceedings of the Fourth Argentine Symposium on Software Engineering (ASSE 2003)*, volume 32, pages 1666–1141, 2003.

[29] A. Benoit, M. Cole, S. Gilmore, and J. Hillston. Flexible skeletal programming with eSkel. In *Euro-Par 2005 Parallel Processing*, pages 761–770. Springer, 2005.

[30] F. Berman and R. Wolski. The AppLeS Project: A Status Report. In *Proceedings of the 8th NEC Research Symposium*, Berlin, Germany, May 1997.

[31] G. Bilardi, K. T. Herley, A. Pietracaprina, G. Pucci, and P. Spirakis. BSP vs LogP. In *Proceedings of the eighth annual ACM symposium on Parallel algorithms and architectures*, pages 25–32. ACM, 1996.

[32] R. Bird and O. de Moor. *Algebra of Programming*. Prentice-Hall, Inc., Upper Saddle River, NJ, USA, 1997.

[33] K. Birman. The promise, and limitations, of gossip protocols. *ACM SIGOPS Operating Systems Review*, 41(5):8–13, 2007.

[34] H. Bischof, S. Gorlatch, and E. Kitzelmann. Cost optimality and predictability of parallel programming with skeletons. *Parallel Processing Letters*, 13(04):575–587, 2003.

[35] H. Bischof, S. Gorlatch, and R. Leshchinskiy. Generic parallel programming using C++ templates and skeletons. In *Domain-Specific Program Generation*, pages 107–126. Springer, 2004.

[36] R. H. Bisseling. *Parallel Scientific Computation: A Structured Approach Using BSP and MPI.* Oxford University Press, 2004.

[37] R. D. Blumofe, C. F. Joerg, B. C. Kuszmaul, C. E. Leiserson, K. H. Randall, and Y. Zhou. Cilk: An Efficient Multithreaded Runtime System. *Journal of Parallel and Distributed Computing*, 37(1):55 – 69, 1996.

[38] R. D. Blumofe and C. E. Leiserson. Scheduling multithreaded computations by work stealing. *Journal of the ACM (JACM)*, 46(5):720–748, 1999.

[39] B. Bohnenstiehl, A. Stillmaker, J. Pimentel, T. Andreas, B. Liu, A. Tran, E. Adeagbo, and B. Baas. Kilocore: A 32 nm 1000-processor array. In *IEEE HotChips Symposium on High-Performance Chips*, Aug. 2016.

[40] A. R. D. Bois. *Mobile Computation in a Purely Functional Language.* PhD thesis, School of Mathematical and Computer Science,Heriot-Watt University, United Kingdom, Aug 2005.

[41] R. Bolze, F. Cappello, E. Caron, M. Daydé, F. Desprez, E. Jeannot, Y. Jégou, S. Lanteri, J. Leduc, N. Melab, et al. Grid'5000: a large scale and highly reconfigurable experimental grid testbed. *International Journal of High Performance Computing Applications*, 20(4):481–494, 2006.

[42] J. L. Bosque and L. Pastor. A Parallel Computational Model for Heterogeneous Clusters. *IEEE Trans. Parallel Distrib. Syst.*, 17(12):1390–1400, Dec. 2006.

[43] G. H. Botorog and H. Kuchen. Skil: An imperative language with algorithmic skeletons for efficient distributed programming. In *High Performance Distributed Computing, 1996., Proceedings of 5th IEEE International Symposium on*, pages 243–252. IEEE, 1996.

[44] T. A. Bratvold. *Skeleton-based parallelisation of functional programs.* PhD thesis, Heriot-Watt University, 1994.

[45] T. D. Braun, H. J. Siegel, N. Beck, L. L. Blni, M. Maheswaran, A. I. Reuther, J. P. Robertson, M. D. Theys, B. Yao, D. Hensgen, and R. F. Freund. A Comparison of Eleven Static Heuristics for Mapping a Class of Independent Tasks onto Heterogeneous Distributed Computing Systems. *Journal of Parallel and Distributed Computing*, 61(6):810 – 837, 2001.

[46] C. Brown, M. Danelutto, K. Hammond, P. Kilpatrick, and A. Elliott. Cost-Directed Refactoring for Parallel Erlang Programs. *International Journal of Parallel Programming*, 42(4):564–582, 2014.

[47] A. Buss, I. Papadopoulos, O. Pearce, T. Smith, G. Tanase, N. Thomas, X. Xu, M. Bianco, N. M. Amato, L. Rauchwerger, et al. STAPL: standard template adaptive parallel library. In *Proceedings of the 3rd Annual Haifa Experimental Systems Conference*, page 14. ACM, 2010.

[48] D. R. Butenhof. *Programming with POSIX Threads*. Addison-Wesley Longman Publishing Co., Inc., Boston, MA, USA, 1997.

[49] R. Buyya. *High Performance Cluster Computing: Programming and Applications , Volume 2*. Prentice Hall PTR, Upper Saddle River, NJ, USA, 1st edition, 1999.

[50] D. K. G. Campbell. *Clumps: A Candidate Model Of Efficient, General Purpose Parallel Computation*. PhD thesis, Department of Computer Science, University of Exeter, United Kingdom, Oct 1994.

[51] D. Caromel and M. Leyton. Fine tuning algorithmic skeletons. In *Euro-Par 2007 Parallel Processing*, pages 72–81. Springer, 2007.

[52] A. Carzaniga, G. P. Picco, and G. Vigna. Designing distributed applications with mobile code paradigms. In *Proceedings of the 19th international conference on Software engineering*, ICSE '97, pages 22–32, New York, NY, USA, 1997. ACM.

[53] H. Casanova, A. Legrand, and M. Quinson. SimGrid: A Generic Framework for Large-Scale Distributed Experiments. In *Computer Modeling and Simula-*

tion, 2008. UKSIM 2008. Tenth International Conference on, pages 126–131. IEEE, 2008.

[54] T. L. Casavant and J. G. Kuhl. A Taxonomy of Scheduling in General-purpose Distributed Computing Systems. *IEEE Trans. Softw. Eng.*, 14(2):141–154, Feb. 1988.

[55] M. Chalabine and C. Kessler. Parallelisation of sequential programs by invasive composition and aspect weaving. In *Advanced Parallel Processing Technologies*, pages 131–140. Springer, 2005.

[56] B. Chamberlain, D. Callahan, and H. Zima. Parallel Programmability and the Chapel Language. *Int. J. High Perform. Comput. Appl.*, 21(3):291–312, Aug. 2007.

[57] B. Chapman, G. Jost, and R. v. d. Pas. *Using OpenMP: Portable Shared Memory Parallel Programming (Scientific and Engineering Computation)*. The MIT Press, 2007.

[58] S. Chatterjee and A. S. Hadi. *Regression analysis by example*. John Wiley & Sons, 2015.

[59] N. Chechina, P. King, and P. Trinder. Redundant movements in autonomous mobility: Experimental and theoretical analysis. *Journal of Parallel and Distributed Computing*, 71(10):1278–1292, 2011.

[60] G. S. Choi, J.-H. Kim, D. Ersoz, A. B. Yoo, and C. R. Das. Coscheduling in clusters: Is it a viable alternative? In *Proceedings of the 2004 ACM/IEEE conference on Supercomputing*, page 16. IEEE Computer Society, 2004.

[61] P. Ciechanowicz and H. Kuchen. Enhancing Muesli's Data Parallel Skeletons for Multi-core Computer Architectures. In *High Performance Computing and Communications (HPCC), 2010 12th IEEE International Conference on*, pages 108–113. IEEE, 2010.

[62] P. Ciechanowicz, M. Poldner, and H. Kuchen. The Münster skeleton library Mueslia comprehensive overview (2009). Technical report, ERCIS Working Paper.

[63] C. Coarfa, Y. Dotsenko, J. Mellor-Crummey, F. Cantonnet, T. El-Ghazawi, A. Mohanti, Y. Yao, and D. Chavarría-Miranda. An Evaluation of Global Address Space Languages: Co-array Fortran and Unified Parallel C. In *Proceedings of the Tenth ACM SIGPLAN Symposium on Principles and Practice of Parallel Programming*, PPoPP '05, pages 36–47, New York, NY, USA, 2005. ACM.

[64] J. Cohen and A. Weitzman. Software Tools for Micro-analysis of Programs. *Softw. Pract. Exper.*, 22(9):777–808, Sept. 1992.

[65] M. Cole. *Algorithmic skeletons: structured management of parallel computation*. Research monographs in parallel and distributed computing. Pitman, 1989.

[66] M. Cole. eSkel: The edinburgh Skeleton library. *Tutorial Introduction. Internal Paper, School of Informatics, University of Edinburgh*, 2002.

[67] M. Cole. Bringing skeletons out of the closet: a pragmatic manifesto for skeletal parallel programming. *Parallel computing*, 30(3):389–406, 2004.

[68] M. I. Cole. Parallel programming with list homomorphisms. *Parallel Processing Letters*, 5(02):191–203, 1995.

[69] R. Cole and O. Zajicek. The APRAM: Incorporating Asynchrony into the PRAM Model. In *Proceedings of the First Annual ACM Symposium on Parallel Algorithms and Architectures*, SPAA '89, pages 169–178, New York, NY, USA, 1989. ACM.

[70] S. A. Cook and R. A. Reckhow. Time-bounded Random Access Machines. In *Proceedings of the Fourth Annual ACM Symposium on Theory of Computing*, STOC '72, pages 73–80, New York, NY, USA, 1972. ACM.

[71] D. Culler, R. Karp, D. Patterson, A. Sahay, K. E. Schauser, E. Santos, R. Subramonian, and T. von Eicken. LogP: Towards a Realistic Model of Parallel Computation. *SIGPLAN Not.*, 28(7):1–12, July 1993.

[72] M. Danelutto and M. Aldinucci. Algorithmic skeletons meeting grids. *Parallel Computing*, 32(7):449–462, 2006.

[73] M. Danelutto, R. Di Meglio, S. Orlando, S. Pelagatti, and M. Vanneschi. A methodology for the development and the support of massively parallel programs. *Future Generation Computer Systems*, 8(1):205–220, 1992.

[74] M. Danelutto and M. Stigliani. SKElib: parallel programming with skeletons in C. In *Euro-Par 2000 Parallel Processing*, pages 1175–1184. Springer, 2000.

[75] M. Danelutto and M. Torquati. Loop parallelism: a new skeleton perspective on data parallel patterns. In *Parallel, Distributed and Network-Based Processing (PDP), 2014 22nd Euromicro International Conference on*, pages 52–59. IEEE, 2014.

[76] J. Darlington, A. J. Field, P. G. Harrison, P. H. J. Kelly, D. W. N. Sharp, and Q. Wu. Parallel Programming Using Skeleton Functions. In *Proceedings of the 5th International PARLE Conference on Parallel Architectures and Languages Europe*, PARLE '93, pages 146–160, London, UK, 1993. Springer-Verlag.

[77] J. Darlington, Y.-k. Guo, H. W. To, and J. Yang. Functional skeletons for parallel coordination. In *EURO-PAR'95 Parallel Processing*, pages 55–66. Springer, 1995.

[78] P. De la Torre and C. P. Kruskal. Submachine locality in the bulk synchronous setting. In *Euro-Par'96 Parallel Processing*, pages 352–358. Springer, 1996.

[79] J. Dean and S. Ghemawat. MapReduce: simplified data processing on large clusters. *Communications of the ACM*, 51(1):107–113, 2008.

[80] X. Y. Deng. *Cost-Driven Autonomous Mobility*. PhD thesis, Heriot-Watt University, United Kingdom, May 2007.

[81] X. Y. Deng, G. Michaelson, and P. Trinder. Autonomous Mobility Skeletons. *Parallel Comput.*, 32:463–478, September 2006.

[82] J. Diaz, C. Munoz-Caro, and A. Nino. A Survey of Parallel Programming Models and Tools in the Multi and Many-Core Era. *Parallel and Distributed Systems, IEEE Transactions on*, 23(8):1369–1386, Aug 2012.

[83] M. Dieterle, J. Berthold, and R. Loogen. A skeleton for distributed work pools in eden. In *International Symposium on Functional and Logic Programming*, pages 337–353. Springer, 2010.

[84] M. Dieterle, T. Horstmeyer, J. Berthold, and R. Loogen. Iterating Skeletons. In *Symposium on Implementation and Application of Functional Languages*, pages 18–36. Springer, 2012.

[85] J. Dongarra, I. Foster, G. Fox, W. Gropp, K. Kennedy, L. Torczon, and A. White, editors. *Sourcebook of Parallel Computing*. Morgan Kaufmann Publishers Inc., San Francisco, CA, USA, 2003.

[86] J. J. Dongarra, P. Luszczek, and A. Petitet. The LINPACK Benchmark: past, present and future. *Concurrency and Computation: Practice and Experience*, 15(9):803–820, 2003.

[87] A. J. Dorta, J. A. Gonzalez, C. Rodriguez, and F. De Sande. llc: A parallel skeletal language . *Parallel Processing Letters*, 13(03):437–448, 2003.

[88] F. Douglis and J. Ousterhout. Transparent Process Migration: Design Alternatives and the Sprite Implementation. *Software: Practice and Experience*, 21(8):757–785, 1991.

[89] A. R. Du Bois, P. Trinder, and H.-W. Loidl. Towards Mobility Skeletons. *Parallel Processing Letters*, 15(03):273–288, 2005.

[90] O. Dubuisson, J. Gustedt, and E. Jeannot. Validating Wrekavoc: a tool for heterogeneity emulation. In *Parallel & Distributed Processing, 2009. IPDPS 2009. IEEE International Symposium on*, pages 1–12. IEEE, 2009.

[91] J. Dünnweber and S. Gorlatch. HOC-SA: A grid service architecture for higher-order components. In *Services Computing, 2004.(SCC 2004). Proceedings. 2004 IEEE International Conference on*, pages 288–294. IEEE, 2004.

[92] D. L. Eager, E. D. Lazowska, and J. Zahorjan. Adaptive load sharing in homogeneous distributed systems. *IEEE Trans. Softw. Eng.*, 12:662–675, May 1986.

[93] H. El-Rewini and M. Abd-El-Barr. *Advanced Computer Architecture and Parallel Processing (Wiley Series on Parallel and Distributed Computing)*. Wiley-Interscience, 2005.

[94] J. Enmyren and C. W. Kessler. SkePU: a multi-backend skeleton programming library for multi-GPU systems. In *Proceedings of the Fourth International Workshop on High-level Parallel Programming and Applications*, pages 5–14. ACM, 2010.

[95] Y. Etsion and D. G. Feitelson. User-level communication in a system with gang scheduling. In *Parallel and Distributed Processing Symposium., Proceedings 15th International*. IEEE, 2001.

[96] J. Faik. *A model for resource-aware load balancing on heterogeneous and non-dedicated clusters*. PhD thesis, Rensselaer Polytechnic Institute, 2005.

[97] J. Falcou, J. Sérot, T. Chateau, and J.-T. Lapresté. QUAFF: efficient C++ design for parallel skeletons. *Parallel Computing*, 32(7):604–615, 2006.

[98] J. a. F. Ferreira, J. a. L. Sobral, and A. J. Proenca. JaSkel: A Java Skeleton-Based Framework for Structured Cluster and Grid Computing. In *CCGRID '06: Proceedings of the Sixth IEEE International Symposium on Cluster Computing and the Grid (CCGRID'06)*, volume 1, pages 301–304. IEEE, 2006.

[99] J. Fischer, S. Gorlatch, and H. Bischof. *Foundations of Data-parallel Skeletons*, pages 1–27. Springer, London, UK, 2003.

[100] M. Flynn. Some Computer Organizations and Their Effectiveness. *Computers, IEEE Transactions on*, C-21(9):948–960, Sept 1972.

[101] S. Fortune and J. Wyllie. Parallelism in Random Access Machines. In *Proceedings of the Tenth Annual ACM Symposium on Theory of Computing*, STOC '78, pages 114–118, New York, NY, USA, 1978. ACM.

[102] I. Foster. What is the Grid? A Three Point Checklist. *GRIDtoday*, 1(6), June 2002.

[103] I. Foster and C. Kesselman. *The Grid 2: Blueprint for a New Computing Infrastructure*. Morgan Kaufmann Publishers Inc., San Francisco, CA, USA, 2003.

[104] I. Foster, J. Vockler, M. Wilde, and Y. Zhao. Chimera: A virtual data system for representing, querying, and automating data derivation. In *Scientific and Statistical Database Management, 2002. Proceedings. 14th International Conference on*, pages 37–46. IEEE, 2002.

[105] A. Fuggetta, G. P. Picco, and G. Vigna. Understanding Code Mobility. *IEEE Trans. Softw. Eng.*, 24:342–361, May 1998.

[106] F. Gava. BSP functional programming: Examples of a cost based methodology. In *Computational Science–ICCS 2008*, pages 375–385. Springer, 2008.

[107] J. Gehring and A. Reinefeld. MARS: A framework for minimizing the job execution time in a metacomputing environment. *Future Generation Computer Systems*, 12(1):87 – 99, 1996.

[108] S. Ghemawat, H. Gobioff, and S.-T. Leung. The Google file system. In *ACM SIGOPS operating systems review*, volume 37, pages 29–43. ACM, 2003.

[109] L. F. W. Góes, C. P. Ribeiro, M. Castro, J.-F. Méhaut, M. Cole, and M. Cintra. Automatic skeleton-driven memory affinity for transactional worklist applications. *International Journal of Parallel Programming*, 42(2):365–382, 2014.

[110] H. Gonzalez-Velez and M. Cole. An adaptive parallel pipeline pattern for grids. In *Parallel and Distributed Processing, 2008. IPDPS 2008. IEEE International Symposium on*, pages 1–11. IEEE, 2008.

[111] H. González-Vélez and M. Leyton. A Survey of Algorithmic Skeleton Frameworks: High-level Structured Parallel Programming Enablers. *Softw. Pract. Exper.*, 40(12):1135–1160, Nov. 2010.

[112] W. Gropp, E. Lusk, and A. Skjellum. *Using MPI: Portable Parallel Programming with the Message-passing Interface*. MIT Press, Cambridge, MA, USA, 1999.

[113] E. Hagersten, A. Landin, and S. Haridi. DDM: A Cache-Only Memory Architecture. *Computer*, 25(9):44–54, Sep 1992.

[114] K. Hammond, J. Berthold, and R. Loogen. Automatic skeletons in template haskell. *Parallel Processing Letters*, 13(03):413–424, 2003.

[115] K. Hammond and G. Michaelson, editors. *Research Directions in Parallel Functional Programming*. Springer-Verlag, London, UK, UK, 2000.

[116] J. G. Hansen. *Virtual Machine Mobility with Self-Migration*. PhD thesis, Department of Computer Science, University of Copenhagen, Apr 2009.

[117] Y. Hayashi and M. Cole. Automated cost analysis of a parallel maximum segment sum program derivation. *Parallel Processing Letters*, 12(01):95–111, 2002.

[118] S. Hemminger. Network emulation with NetEm. In *Proceedings of the 6th Australia's National Linux Conference (LCA2005)*, pages 18–23, 2005.

[119] J. L. Hennessy and D. A. Patterson. *Computer Architecture, Fifth Edition: A Quantitative Approach*. Morgan Kaufmann Publishers Inc., San Francisco, CA, USA, 5th edition, 2011.

[120] M. Herlihy and N. Shavit. *The Art of Multiprocessor Programming*. Morgan Kaufmann Publishers Inc., San Francisco, CA, USA, 2008.

[121] C. A. Herrmann and C. Lengauer. HDC: A Higher-Order Language for Divide-and-Conquer. *Parallel Processing Letters*, 10(2-3):239–250, 2000.

[122] T. Heywood and S. Ranka. A practical hierarchical model of parallel computation II. Binary tree and FFT algorithms . *Journal of Parallel and Distributed Computing*, 16(3):233 – 249, 1992.

[123] J. M. D. Hill, B. McColl, D. C. Stefanescu, M. W. Goudreau, K. Lang, S. B. Rao, T. Suel, T. Tsantilas, and R. H. Bisseling. BSPlib: The BSP Programming Library, 1998.

[124] A. Holmes. *Hadoop in practice*. Manning Publications Co., 2012.

[125] W.-M. Hwu, K. Keutzer, and T. Mattson. The Concurrency Challenge. *Design Test of Computers, IEEE*, 25(4):312–320, July 2008.

[126] F. Ino, N. Fujimoto, and K. Hagihara. LogGPS: A Parallel Computational Model for Synchronization Analysis. *SIGPLAN Not.*, 36(7):133–142, June 2001.

[127] V. Janjic, C. BROWN, and K. Hammond. Lapedo: Hybrid Skeletons for Programming Heterogeneous Multicore Machines in Erlang. *Parallel Computing: On the Road to Exascale*, 27:185, 2016.

[128] N. Javed and F. Loulergue. Parallel programming and performance predictability with Orléans Skeleton Library. In *High Performance Computing and Simulation (HPCS), 2011 International Conference on*, pages 257–263. IEEE, 2011.

[129] C. B. Jay, M. Cole, M. Sekanina, and P. Steckler. A monadic calculus for parallel costing of a functional language of arrays. In *Euro-Par'97 Parallel Processing*, pages 650–661. Springer, 1997.

[130] N. R. Jennings. An Agent-based Approach for Building Complex Software Systems. *Commun. ACM*, 44(4):35–41, Apr. 2001.

[131] E. Jul, H. Levy, N. Hutchinson, and A. Black. Fine-grained Mobility in the Emerald System. *ACM Trans. Comput. Syst.*, 6(1):109–133, Feb. 1988.

[132] B. H. Juurlink and H. A. Wijshoff. The E-BSP Model: Incorporating general locality and unbalanced communication into the BSP Model. In *Euro-Par'96 Parallel Processing*, pages 339–347. Springer, 1996.

[133] B. H. H. Juurlink and H. A. G. Wijshoff. A Quantitative Comparison of Parallel Computation Models. *ACM Trans. Comput. Syst.*, 16(3):271–318, Aug. 1998.

[134] S. Kannan, M. Roberts, P. Mayes, D. Brelsford, and J. F. Skovira. Workload management with loadleveler. *IBM Redbooks*, 2:2, 2001.

[135] A. Kao and S. R. Poteet. *Natural language processing and text mining*. Springer Science & Business Media, 2007.

[136] Y. Karasawa and H. Iwasaki. A parallel skeleton library for multi-core clusters. In *Parallel Processing, 2009. ICPP'09. International Conference on*, pages 84–91. IEEE, 2009.

[137] H. Karau, A. Konwinski, P. Wendell, and M. Zaharia. *Learning spark: lightning-fast big data analysis*. " O'Reilly Media, Inc.", 2015.

[138] H. Kasim, V. March, R. Zhang, and S. See. Survey on Parallel Programming Model. In *Proceedings of the IFIP International Conference on Network and Parallel Computing*, NPC '08, pages 266–275, Berlin, Heidelberg, 2008. Springer-Verlag.

[139] J. O. Kephart and D. M. Chess. The Vision of Autonomic Computing. *Computer*, 36(1):41–50, Jan. 2003.

[140] B. W. Kernighan, D. M. Ritchie, and P. Ejeklint. *The C programming language*, volume 2. prentice-Hall Englewood Cliffs, 1988.

[141] K. Krauter, R. Buyya, and M. Maheswaran. A taxonomy and survey of grid resource management systems for distributed computing. *Software-Practice and Experience*, 32(2):135–64, 2002.

[142] Z. D. Krl. *Mobile Computation with Functions*. PhD thesis, Laboratory for Foundations of Computer Science, University of Edinburgh, Edinburgh, UK, 2001.

[143] D. B. Lange and M. Oshima. Seven good reasons for mobile agents. *Commun. ACM*, 42:88–89, March 1999.

[144] D. Lavenier et al. PLAST: parallel local alignment search tool for database comparison. *BMC bioinformatics*, 10(1):1, 2009.

[145] K. Lee, N. W. Paton, R. Sakellariou, E. Deelman, A. A. Fernandes, and G. Mehta. Adaptive workflow processing and execution in pegasus. *Concurrency and Computation: Practice and Experience*, 21(16):1965–1981, 2009.

[146] J. Legaux, Z. Hu, F. Loulergue, K. Matsuzaki, and J. Tesson. Programming with BSP homomorphisms. In *Euro-Par 2013 Parallel Processing*, pages 446–457. Springer, 2013.

[147] D. Leijen, W. Schulte, and S. Burckhardt. The design of a task parallel library. In *Acm Sigplan Notices*, volume 44, pages 227–242. ACM, 2009.

[148] X. Leroy, D. Doligez, A. Frisch, J. Garrigue, D. Rémy, and J. Vouillon. The OCaml system release 4.02. *Institut National de Recherche en Informatique et en Automatique*, 2014.

[149] M. Leyton and J. M. Piquer. Skandium: Multi-core programming with algorithmic skeletons. In *Parallel, Distributed and Network-Based Processing (PDP), 2010 18th Euromicro International Conference on*, pages 289–296. IEEE, 2010.

[150] H. Liu. A Component-Based Programming Model for Autonomic Applications. In *Proceedings of the First International Conference on Autonomic Comput-*

ing, ICAC '04, pages 10–17, Washington, DC, USA, 2004. IEEE Computer Society.

[151] H.-W. Loidl. *Granularity in Large-Scale Parallel Functional Programming*. PhD thesis, Department of Computing Science, University of Glasgow, Mar. 1998.

[152] R. Loogen, Y. Ortega-Mallén, and R. Peña-Marí. Parallel functional programming in Eden. *Journal of Functional Programming*, 15(03):431–475, 2005.

[153] F. Loulergue. Parallel juxtaposition for bulk synchronous parallel ML. In *Euro-Par 2003 Parallel Processing*, pages 781–788. Springer, 2003.

[154] U. Lublin and D. G. Feitelson. The workload on parallel supercomputers: modeling the characteristics of rigid jobs. *Journal of Parallel and Distributed Computing*, 63(11):1105–1122, 2003.

[155] B. Maggs, L. Matheson, and R. Tarjan. Models of parallel computation: a survey and synthesis. In *System Sciences, 1995. Proceedings of the Twenty-Eighth Hawaii International Conference on*, volume 2, pages 61–70, Jan 1995.

[156] S. Makineni and R. Iyer. Measurement-based Analysis of TCP/IP Processing Requirements. In *10th International Conference on High Performance Computing (HiPC 2003), Hyderabad, India.*, 2003.

[157] A. Marletta. cpulimit, May 2012, https://github.com/opsengine/cpulimit.

[158] R. Marques, H. Paulino, F. Alexandre, and P. D. Medeiros. Algorithmic skeleton framework for the orchestration of GPU computations. In *Euro-Par 2013 Parallel Processing*, pages 874–885. Springer, 2013.

[159] M. Marr. *Descriptive simplicity in parallel computing*. PhD thesis, University of Edinburgh. College of Science and Engineering. School of Informatics., 1997.

[160] K. Matsuzaki and K. Emoto. Implementing fusion-equipped parallel skeletons by expression templates. In *Implementation and Application of Functional Languages*, pages 72–89. Springer, 2010.

[161] K. Matsuzaki, Z. Hu, and M. Takeichi. Parallelization with tree skeletons. In *European Conference on Parallel Processing*, pages 789–798. Springer, 2003.

[162] K. Matsuzaki, H. Iwasaki, K. Emoto, and Z. Hu. A library of constructive skeletons for sequential style of parallel programming. In *Proceedings of the 1st international conference on Scalable information systems*, page 13. ACM, 2006.

[163] T. Mattson, B. Sanders, and B. Massingill. *Patterns for Parallel Programming*. Addison-Wesley Professional, 2004.

[164] T. G. Mattson, M. Riepen, T. Lehnig, P. Brett, W. Haas, P. Kennedy, J. Howard, S. Vangal, N. Borkar, G. Ruhl, et al. The 48-core SCC processor: the programmer's view. In *Proceedings of the 2010 ACM/IEEE International Conference for High Performance Computing, Networking, Storage and Analysis*, pages 1–11. IEEE Computer Society, 2010.

[165] H. Menon and L. Kalé. A Distributed Dynamic Load Balancer for Iterative Applications. In *Proceedings of the International Conference on High Performance Computing, Networking, Storage and Analysis*, SC '13, pages 15:1–15:11, New York, NY, USA, 2013. ACM.

[166] A. Merlin and G. Hains. A Generic Cost Model for Concurrent and Data-parallel Meta-computing. *Electronic Notes in Theoretical Computer Science*, 128(6):3 – 19, 2005. Proceedings of the Fouth International Workshop on Automated Verification of Critical Systems (AVoCS 2004).

[167] G. Michaelson. Dynamic Farm Skeleton Task Allocation Through Task Mobility. In *Proceedings of the International Conference on Parallel and Distributed Processing Techniques and Applications (PDPTA)*, volume 1, pages 262–232. The Steering Committee of The World Congress in Computer Science, Computer Engineering and Applied Computing (WorldComp), 2012.

[168] R. Miller and L. Boxer. *Algorithms Sequential & Parallel: A Unified Approach*. An Alan R. Apt book. Prentice Hall, 2000.

[169] D. Milojici, F. Douglis, and R. Wheeler. *Mobility: processes, computers, and agents*. ACM Press/Addison-Wesley Publishing Co., New York, NY, USA, 1999.

[170] K. Morita, A. Morihata, K. Matsuzaki, Z. Hu, and M. Takeichi. Automatic inversion generates divide-and-conquer parallel programs. In *ACM SIGPLAN Notices*, volume 42, pages 146–155. ACM, 2007.

[171] R. Murch. *Autonomic Computing*. IBM Press, 2004.

[172] C. S. R. Murthy and G. Manimaran. *Resource Management in Real-Time Systems and Networks*. MIT Press, Cambridge, MA, USA, 2001.

[173] S. Nagar, A. Banerjee, A. Sivasubramaniam, and C. R. Das. Alternatives to coscheduling a network of workstations. *Journal of Parallel and Distributed Computing*, 59(2):302–327, 1999.

[174] NAS Parallel Benchmarks, Oct 2015, https://www.nas.nasa.gov /publications/npb.html.

[175] B. Nichols, D. Buttlar, and J. Farrell. *Pthreads programming: A POSIX standard for better multiprocessing*. O'Reilly Media, Inc., 1996.

[176] J. Nickolls, I. Buck, M. Garland, and K. Skadron. Scalable Parallel Programming with CUDA. *Queue*, 6(2):40–53, Mar. 2008.

[177] H. Nishikawa and P. Steenkiste. A general architecture for load balancing in a distributed-memory environment. In *Distributed Computing Systems, 1993., Proceedings the 13th International Conference on*, pages 47–54, May 1993.

[178] J. Owens, M. Houston, D. Luebke, S. Green, J. Stone, and J. Phillips. GPU Computing. *Proceedings of the IEEE*, 96(5):879–899, May 2008.

[179] D. Padua. *Encyclopedia of parallel computing*, volume 4. Springer Science & Business Media, 2011.

[180] D. Pasetto and M. Vanneschi. Machine-independent analytical models for cost evaluation of template-based programs. In *PDP*, pages 485–492. IEEE Computer Society, 1997.

[181] D. A. Patterson and J. L. Hennessy. *Computer Organization and Design: The Hardware/Software Interface (The Morgan Kaufmann Series in Computer Architecture and Design)*. Morgan Kaufmann Publishers Inc., San Francisco, CA, USA, 4th edition, 2008.

[182] S. Perarnau and G. Huard. KRASH: Reproducible CPU load generation on many-core machines. In *Parallel & Distributed Processing (IPDPS), 2010 IEEE International Symposium on*, pages 1–10. IEEE, 2010.

[183] A. D. Pereira, L. Ramos, and L. F. Góes. PSkel: A stencil programming framework for CPU-GPU systems. *Concurrency and Computation: Practice and Experience*, 2015.

[184] E. Pitt and K. McNiff. *Java. RMI: The Remote Method Invocation Guide*. Addison-Wesley Longman Publishing Co., Inc., 2001.

[185] J. Protic, M. Tomasevic, and V. Milutinovic. Distributed shared memory: concepts and systems. *Parallel Distributed Technology: Systems Applications, IEEE*, 4(2):63–71, Summer 1996.

[186] K. Qureshi and M. Hatanaka. An introduction to load balancing for parallel raytracing on HDC systems. *Current Science, Tutorials*, 78(7):818 – 820, 2000.

[187] F. A. Rabhi and S. Gorlatch, editors. *Patterns and Skeletons for Parallel and Distributed Computing*. Springer-Verlag, London, UK, 2003.

[188] R. Rangaswami. *A Cost Analysis for a Higher-order Parallel Programming Model*. PhD thesis, Department of Computing Science, University of Edinburgh, 1996.

[189] C. Ranger, R. Raghuraman, A. Penmetsa, G. Bradski, and C. Kozyrakis. Evaluating mapreduce for multi-core and multiprocessor systems. In *High Perfor-*

mance Computer Architecture, 2007. HPCA 2007. IEEE 13th International Symposium on, pages 13–24. Ieee, 2007.

[190] M. Reid-Miller, G. L. Miller, and F. Modugno. List Ranking and Parallel Tree Contraction. In J. Reif, editor, *Synthesis of Parallel Algorithms*, chapter 3, pages 115–194. Morgan Kaufmann, 1993.

[191] J. Reinders. *Intel threading building blocks: outfitting C++ for multi-core processor parallelism*. O'Reilly Media, Inc., 2007.

[192] R. Reiner. Next Generation Packet Processing: RM9000x2 Integrated Multiprocessor with Hypertransport. In *Platform Conference, PMC-Sierra*, pages 1–17, Jan 2002.

[193] B. Reistad and D. K. Gifford. Static Dependent Costs for Estimating Execution Time. *SIGPLAN Lisp Pointers*, VII(3):65–78, July 1994.

[194] R. Reyes, A. J. Dorta, F. Almeida, and F. de Sande. Automatic hybrid mpi+ openmp code generation with llc. In *European Parallel Virtual Machine/Message Passing Interface Users Group Meeting*, pages 185–195. Springer, 2009.

[195] S. Russell and P. Norvig. *Artificial Intelligence: A Modern Approach*. Prentice Hall series in artificial intelligence. Prentice Hall, 2010.

[196] T. Sakamoto, T. Sekiguchi, and A. Yonezawa. Bytecode transformation for portable thread migration in Java. In *Agent Systems, Mobile Agents, and Applications*, pages 16–28. Springer, 2000.

[197] S. Sato and K. Matsuzaki. A Generic Implementation of Tree Skeletons. *International Journal of Parallel Programming*, 44(3):686–707, 2016.

[198] J. Sérot and D. Ginhac. Skeletons for parallel image processing: an overview of the skipper project. *Parallel computing*, 28(12):1685–1708, 2002.

[199] M. Sheikhalishahi, L. Grandinetti, R. M. Wallace, and J. L. Vazquez-Poletti. Autonomic resource contention-aware scheduling. *Software: Practice and Experience*, 45(2):161–175, 2015.

[200] B. Shirazi, M. Wang, and G. Pathak. Analysis and evaluation of heuristic methods for static task scheduling. *Journal of Parallel and Distributed Computing*, 10(3):222–232, 1990.

[201] B. A. Shirazi, K. M. Kavi, and A. R. Hurson, editors. *Scheduling and Load Balancing in Parallel and Distributed Systems*. IEEE Computer Society Press, Los Alamitos, CA, USA, 1995.

[202] N. G. Shivaratri, P. Krueger, and M. Singhal. Load distributing for locally distributed systems. *Computer*, 25(12):33–44, 1992.

[203] J. Singler, P. Sanders, and F. Putze. MCSTL: The multi-core standard template library. In *Euro-Par 2007 Parallel Processing*, pages 682–694. Springer, 2007.

[204] D. B. Skillicorn and W. Cai. A cost calculus for parallel functional programming. *Journal of Parallel and Distributed Computing*, 28(1):65–83, 1995.

[205] D. B. Skillicorn, J. Hill, and W. F. McColl. Questions and answers about BSP. *Scientific Programming*, 6(3):249–274, 1997.

[206] M. Snir. *MPI–the Complete Reference: The MPI core*, volume 1. MIT press, 1998.

[207] M. Sottile, T. G. Mattson, and C. E. Rasmussen. *Introduction to Concurrency in Programming Languages*. Chapman & Hall/CRC, 1st edition, 2009.

[208] A. Stegmeier, M. Frieb, R. Jahr, and T. Ungerer. Algorithmic skeletons for parallelization of embedded real-time systems. In *submitted to 3rd Workshop on High-performance and Real-time Embedded Systems (HiRES)*, 2015.

[209] T. Sterling, D. J. Becker, D. Savarese, J. E. Dorband, U. A. Ranawake, and C. V. Packer. Beowulf: A Parallel Workstation For Scientific Computation. In *In Proceedings of the 24th International Conference on Parallel Processing*, pages 11–14, Urbana-Champain, Illinois, USA, 1995. CRC Press.

[210] M. Steuwer, P. Kegel, and S. Gorlatch. Skelcl-a portable skeleton library for high-level gpu programming. In *Parallel and Distributed Processing Workshops and Phd Forum (IPDPSW), 2011 IEEE International Symposium on*, pages 1176–1182. IEEE, 2011.

[211] J. Stewart, P. Nixon, T. Walsh, and I. Ferguson. Towards Strong Mobility in the Shared Source CLI. In *Communicating Process Architectures*, pages 363–373, 2005.

[212] J. E. Stone, D. Gohara, and G. Shi. OpenCL: A parallel programming standard for heterogeneous computing systems. *Computing in Science & Engineering*, 12(1-3):66–73, 2010.

[213] X.-H. Sun and D. T. Rover. Scalability of parallel algorithm-machine combinations. *Parallel and Distributed Systems, IEEE Transactions on*, 5(6):599–613, 1994.

[214] K. P. Sycara. The Many Faces of Agents. *AI Magazine*, 19(2):11–12, 1998.

[215] A. S. Tanenbaum and H. Bos. *Modern operating systems*. Prentice Hall Press, 2014.

[216] A. S. Tanenbaum and M. v. Steen. *Distributed Systems: Principles and Paradigms (2Nd Edition)*. Prentice-Hall, Inc., Upper Saddle River, NJ, USA, 2006.

[217] P. Tosic and G. Agha. Towards a hierarchical taxonomy of autonomous agents. In *Systems, Man and Cybernetics, 2004 IEEE International Conference on*, volume 4, pages 3421–3426 vol.4, Oct 2004.

[218] M. Trenti and P. Hut. N-body simulations (gravitational). *Scholarpedia*, 3(5):3930, 2008.

[219] P. W. Trinder, M. I. Cole, K. Hammond, H.-W. Loidl, and G. J. Michaelson. Resource analyses for parallel and distributed coordination. *Concurrency and Computation: Practice and Experience*, 25(3):309–348, 2013.

[220] UPC Consortium. UPC Language Specifications, v1.2. Tech Report LBNL-59208, Lawrence Berkeley National Lab, 2005.

[221] L. G. Valiant. A bridging model for parallel computation. *Communications of the ACM*, 33(8):103–111, 1990.

[222] L. G. Valiant. A Bridging Model for Multi-core Computing. *J. Comput. Syst. Sci.*, 77(1):154–166, Jan. 2011.

[223] M. Vanneschi. The programming model of ASSIST, an environment for parallel and distributed portable applications. *Parallel computing*, 28(12):1709–1732, 2002.

[224] S. Vazhkudai, J. M. Schopf, and I. Foster. Predicting the performance of wide area data transfers. In *Parallel and Distributed Processing Symposium., Proceedings International, IPDPS 2002, Abstracts and CD-ROM*, pages 10–pp. IEEE, 2001.

[225] K. Wang, X. Zhou, T. Li, D. Zhao, M. Lang, and I. Raicu. Optimizing load balancing and data-locality with data-aware scheduling. In *Big Data (Big Data), 2014 IEEE International Conference on*, pages 119–128, Oct 2014.

[226] A. Waterland. stress, 2012. http://people.seas.harvard.edu/ãpw/stress/.

[227] M. Weske and G. Vossen. Workflow languages. In *Handbook on Architectures of Information Systems*, pages 359–379. Springer, 1998.

[228] T. White. *Hadoop: The definitive guide*. O'Reilly Media, Inc., 2012.

[229] P. T. Wojciechowski. *Nomadic Pict: language and infrastructure design for mobile computation*. PhD thesis, University of Cambridge, Computer Laboratory, UK, April 2000.

[230] M. Wooldridge. Agent-based software engineering. *Software Engineering. IEE Proceedings*, 144(1):26–37, Feb 1997.

[231] M. Wooldridge and N. R. Jennings. Intelligent Agents: Theory and Practice. *Knowledge Engineering Review*, 10:115–152, 1995.

[232] E. Wu and Y. Liu. Emerging technology about GPGPU. In *Circuits and Systems, 2008. APCCAS 2008. IEEE Asia Pacific Conference on*, pages 618–622. IEEE, 2008.

[233] C. Xu, F. C. Lau, and R. Diekmann. Decentralized remapping of data parallel applications in distributed memory multiprocessors. *Concurrency - Practice and Experience*, 9(12):1351–1376, 1997.

[234] G. Yaikhom, M. Cole, and S. Gilmore. Combining measurement and stochastic modelling to enhance scheduling decisions for a parallel mean value analysis algorithm. In *Computational Science–ICCS 2006*, pages 929–936. Springer, 2006.

[235] L. T. Yang, X. Ma, and F. Mueller. Cross-platform performance prediction of parallel applications using partial execution. In *Supercomputing, 2005. Proceedings of the ACM/IEEE SC 2005 Conference*, pages 40–40. IEEE, 2005.

[236] F. Zambonelli. How to improve local load balancing policies by distorting load information. In *High Performance Computing, 1998. HIPC'98. 5th International Conference On*, pages 318–325. IEEE, 1998.

[237] A. Zavanella. Skel-BSP: Performance portability for skeletal programming. In *High Performance Computing and Networking*, pages 290–299. Springer, 2000.

[238] S. Zhuravlev, S. Blagodurov, and A. Fedorova. Addressing shared resource contention in multicore processors via scheduling. In *ACM SIGARCH Computer Architecture News*, volume 38, pages 129–142. ACM, 2010.

[239] S. Zhuravlev, J. C. Saez, S. Blagodurov, A. Fedorova, and M. Prieto. Survey of Scheduling Techniques for Addressing Shared Resources in Multicore Processors. *ACM Computing Surveys (CSUR)*, 45(1):1–28, 2012.

[240] A. Y. Zomaya and Y.-H. Teh. Observations on Using Genetic Algorithms for Dynamic Load-Balancing. *IEEE Trans. Parallel Distrib. Syst.*, 12:899–911, September 2001.

[241] J. A. Zukas, W. Walters, and W. P. Walters. *Explosive effects and applications*. Springer Science & Business Media, 2002.

[242] A. Zunino, M. Campo, and C. Mateos. Reactive mobility by failure: When fail means move. *Information Systems Frontiers*, 7(2):141–154, 2005.